A Review of the Noise Uncertainty Impact on Energy Detection with Different OFDM System Designs

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Abstract: Cognitive radio networks (CRN) based on spectrum sensing represent intelligent wireless communication technology dedicated to a more efficient exploitation of the available frequency spectrum. Although the energy detection (ED) method was found to be a promising candidate for spectrum sensing in the CRN, its detection performance is challenged by the noise fluctuations. These fluctuations, known as noise uncertainty (NU), may vary beyond what is estimated due to changes in temperature, interference and filtering. In this work, the influence of NU on the performance of ED for signals transmitted using an orthogonal frequency division multiplexing (OFDM) technique is reviewed. Besides that, thorough analyses are performed by means of extensive simulations of the ED process for three different OFDM system designs based on rate adaptation, margin adaptation and mutual rate and margin adaptation. The analyses presented in this review paper give a systematic insight into how various OFDM modulations, NU levels, probabilities of a false alarm, number of samples used in the ED process and levels of signal-to-noise ratio impact the probability of signal detection and the overall ED performance of different OFDM system designs. The results obtained through simulations show that the trade-off among the parameters analyzed can bring improvements in the ED process of different OFDM system designs. The research challenges for improvement of the main ED weaknesses have been further discussed, with a performance comparison of the ED method with other prominent local spectrum sensing methods. The survey results presented constitute a reference for improvements of the broadly-accepted ED approach.

Keywords: cognitive radio networks; OFDM; energy detection; noise uncertainty; spectrum sensing;

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1. Introduction

In the last decade, fast-growing wireless services have become popular worldwide due to a high demand for information from mobile applications, social networking sites, mobile gaming and mobile video services. Analyses indicate that many licensed wireless spectrum portions are not effectively used and idle in some specific periods of the time and in certain geographical areas [1-2].

According to the reports concerning the inefficiency of the currently fixed spectrum allocation, the academic and industrial sectors open the discussions on intelligent sharing of the licensed and unlicensed spectrum [3]. Cognitive radio networks (CRNs) are proposed as a promising solution which can minimize such inefficient spectrum utilization. CRN represents a new intelligent wireless communication technology whose purpose is the detection of an available frequency spectrum. To solve the inefficiency of a frequency spectrum assignment policy, CRN as technology is based on an approach named “spectrum sensing “. The objective of spectrum sensing is to detect inactivity of the licensed/primary user (PU) in the allocated frequency band and if it is free, make provisions for the unlicensed/secondary user (SU) so that it does not affect the efficiency of the PU. Thus, the utilization of vacant band by the SU can significantly alleviate the spectrum scarcity problem [4].

The licensed band CR uses the spectrum that is especially meant for licensed user access. This CR approach checks PU activity on a certain channel of the spectrum. If the PU is active, then it switches unlicensed users (SUs) to the other channel. If the PU is not active, then it gives access to the unlicensed users (SUs) and monitors the entire channel for the PU. In the case of an unlicensed band, CR uses the unlicensed parts of the spectrum that are available for SUs only. Therefore, there is no need for the cognitive radio to sense the entire spectrum before the SUs use the channel [5].

Spectrum-sensing methods can be classified into different categories, such as coherent and non-coherent detection or cooperative and non-cooperative detection. In the case of coherent detection, a priori knowledge of the PU signal is required to detect spectrum holes, while non-coherent detection is performed without the need for a priori knowledge of the PU signal [6-7]. Based on this classification, literature has proposed a variety of spectrum-sensing methods, and the most prominent ones are *energy detection, matched filter detection, cyclostationary feature detection* and *entropy-based detection* [8-10]. These detection techniques also belong to non-cooperative detection, which is an approach for the detection of PU signals based on the local observations of SU. Other techniques such as *centralized or distributed-approach detection* belong to cooperative detection which refers to spectrum-sensing methods that enable multiple SUs to share their local sensing information for more accurate PU detection [11].

Among all the aforementioned spectrum-sensing techniques, *energy detection* (ED) has the advantages of low complexity and cost. Thus, it is especially suitable for wideband spectrum sensing. For that reason, ED as a non-coherent and non-cooperative technique is broadly accepted as the most commonly used technique for spectrum sensing in CRN, which supports the use of the ED technique for further analyses in this work.

The ED technique is the semi-blind process which does not require information about wireless channel gains and other parameter estimates concerning PU signal, and only exact information about noise power at the position of the SU is needed for an accurate detection of the PU. However, accurate noise power estimation is not always possible, since noise may be impacted by the effects from various sources such as thermal noise, filtering effects, radio-frequency circuits and the interference caused by other signals. Such effects affect noise power estimation which causes the estimation error referred to as noise uncertainty (NU) [9]. Although ED is found to be a promising candidate for spectrum sensing in CRNs, its detection performance can be significantly challenged by the NU [12]. Hence, this paper has presented trade-off analyses concerning the impact of NU on ED performance.

Orthogonal frequency-division multiplexing (OFDM) is seen as a promising candidate to be used in CRNs because of its capability to mitigate inter-symbol interference (ISI) and combat multipath fading using a cyclic prefix (CP) [13-15]. OFDM has become the modulation of choice in many contemporary broadband communication systems. Different modulation schemes are used in OFDM systems including Binary Phase Shift Keying (B-PSK), Quadrature Phase-Shift Keying (Q-PSK), 16-Quadrature Amplitude Modulation (16-QAM) and 64/128/256/1024/ … -QAM. The selection of the best modulation technique depends upon signal-to-noise ratio (SNR), Bit Error Rate (BER), cost-effectiveness and the ability to provide specific data rates [16, 17]. OFDM systems are designed based on three different approaches, namely the rate-adaptive (RA) approach which tends to maximize the transmission rate under BER and transmit (Tx) power constraint, the margin-adaptive (MA) approach which tends to minimize Tx power under BER and the transmission rate constraint and mutual RA and MA approach which jointly optimize the transmission rate and Tx power under BER constraint. Each of these OFDM system design approaches impacts the ED process in CRNs in its own particular way.

Hence, this review work analyzes the influence of NU on ED performance for transmitting signals using different OFDM system designs. Analyses are performed based on developed algorithms which enable extensive simulations of ED performance for the OFDM signals impacted by NU. The major contribution of this work is a fundamental trade-off evaluation concerning how parameters such as probabilities of a false alarm, OFDM modulations, number of samples used in the ED process, Tx power of PU, levels of SNR at position of SU, and values of NUs impact the probability of PU signal detection in the ED process for three different OFDM system designs.

The paper is structured as follows: Section 2 gives an overview of the work on noise estimation and NU impact on ED of OFDM signals. Descriptions of different OFDM system designs and communication technologies which use OFDM as a transmission technique are given in Section 3. Basic spectrum-sensing model based on ED of signals without NU is introduced in Section 4. In Section 5, a more realistic spectrum-sensing model which takes into account the impact of NU on the probability of ED is presented. Developed algorithms for simulating ED of OFDM signals impacted by different levels of NUs are described in Section 6. The results of the simulations obtained for ED of OFDM signals are presented and discussed in Section 7. Section 8 is dedicated to the discussion related to future research challenges for improving the ED method considering the simulation results obtained presented in Section 7. Finally, some concluding remarks are given in Section 9.

2. Related work on noise estimation and NU impact on ED of OFDM signals

The CR paradigm was first introduced in seminal work [18] and ED as a method for spectrum sensing of unknown deterministic signals was first introduced in [19]. The methods for PU detection in CRN may be strongly degraded by the NU. As shown in [20], closed-form probability distribution functions for a single noise sample and the energy of multiple noise samples are derived, allowing an optimal Neyman-Pearson detector to be employed when NU is present. In [12], the decision rules for the ED technique in the presence of NU are derived. Compared with the conventional decision rules obtained by overestimating the noise power, the proposed decision rules provide performance gains in terms of SNR.

The modeling of the NU impact on the level of SNR wall below which ED will fail to be robust, no matter how long the channel will be observed, was introduced in [21, 22]. Some of the first analyses related to the ED performance under various discrete and continuous models of NU are analyzed in [23], based on that a design of energy detector is put forward. The theoretical analysis of the NU modeling with ED is performed in [24] showing that the bounded NU approximation model is a specific case of the general unbounded NU approximation model. In addition, a Gaussian model for the inverse noise standard deviation is proposed in [20] and a simulation example confirms that by properly modeling the NU, the SNR wall phenomenon can be avoided, providing useful ED performance at very low SNR.

In [25], the performance of the ED with estimated noise power using the maximum likelihood criterion was analyzed. Authors show that NU itself does not cause the SNR wall phenomenon but is rather caused by the inability to refine the noise power estimation process while the observation time increases. A novel method to estimate the noise power from the received signal samples using a developed algorithm based on a high-pass filters bank and median filtering is proposed in [26]. The proposed approach ensures maintaining a constant and low false alarm rate in the presence of NU, without increasing the probability of misdetection, even in the low SNR regime and without increasing the number of spectrum-sensing samples.

In [27], the authors proposed the concept of NU estimation which measures the level of noise using a blind technique based on sample covariance matrix eigenvalues of the received signal and noise using the minimum description length criterion. The results they obtained show that such an enhanced ED-based technique decreases the probability of a false alarm and increases the probability of detection. An optimal dynamic stochastic resonance processing method is introduced in [28] to relieve the SNR wall and corresponding NU problems in traditional ED under low SNR circumstances.

Additionally, in [29], the authors study generalized energy detector (GED) performance by replacing the squaring operation of the amplitude of the received signal with an arbitrary positive power operation constant p under NU. The results prove that SNR wall is not dependent on the value of that power constant p. The paper [30] analyzes the impact of noise power calibration effects on the SNR wall problem in coarse spectrum sensing for CR network systems based on proposed GED with an antenna array. The results of the simulation demonstrate that the proposed GED under the NU can reduce the SNR wall problem and achieve a lower probability of error compared to the conventional ED. In [31], the authors study the SNR wall under diversity reception in the presence of the NU and the fading for GED obtained through changing the squaring operation in ED by an arbitrary positive number p. It is shown that above a certain value, the effect of NU is more severe when compared to the fading. It is also shown that the performance is the best for values of arbitrary positive number p close to 2. Fora large value of sample size, the detection performance of GED becomes independent of p.

In [7, 20, 32-35], different OFDM spectrum sensing techniques are analyzed. [7] proposes an ED method of spectrum sensing for OFDM signal and QPSK modulation. The paper analyzes the limitations of the simulated ED method. In particular, it shows how the ED technique can be implemented using the software-defined radio (SDR) and how the sensing performance of an implemented real-time energy detector compares to its simulated equivalent. In [32], the influence of the probability of PU signal detection on the probability of a false alarm was analyzed for the ED technique in case of the BPSK and OFDM-modulated signal in a wireless local area network (WLAN) and Worldwide Interoperability for Microwave Access (WiMAX) system. According to [20, 33], a challenge for the spectrum sensing based on ED is the ability to detect signals at low SNR levels.

To solve the challenge of a difficult ED in low SNR environments, Differential Characteristics (DC), DC – Pilot Tones and DC – Cyclic Prefix based on OFDM spectrum-sensing algorithms are presented in [36]. The results of the simulation illustrate that all three methods can achieve good performance under low SNR with the presence of a timing delay during the sensing process. In [37-39], spectrum-sensing algorithms based on the correlation properties of the OFDM cyclic prefix (CP) are presented. Algorithms for ED proposed in [38, 40] are sensitive to timing offset, while [39] presents the generalized likelihood ratio test with the probability of OFDM signal detection and a false alarm independent of the timing offset.

In [40, 41] an optimal and sub-optimal Neyman-Pearson (NP) spectrum sensing method for detecting OFDM signal based on the feature of the CP is presented. A practical generalized log-likelihood ratio test is used to show that spectrum sensing is sensitive to NU. Mean Ambiguity Function (MAF) as a new spectrum sensing technique of the OFDM signal under NU is proposed in [42]. Through simulations, it is shown that the proposed detector can achieve good detection performance in very low SNR environments, and it is robust to NU. In [43], we have presented the preliminary results concerning the impact of NU on energy misdetection performance of OFDM systems based on a margin (power) adaptive system design. According to the results, NU degrades the performance of ED for OFDM systems which use power-adaptive algorithms.

Although NU has an impact on ED probability, according to our knowledge, this impact has not been thoroughly analyzed for ED of OFDM signals transmitted by means of different OFDM system designs. Hence, in this work, an algorithm for simulating the ED of OFDM modulated signals under versatile NUs and for different OFDM system designs is developed. As far as we know, this is the first review work which offers a comprehensive overview of the impact of Tx power adaptation in MA systems or OFDM modulation order adjustment in RA systems or both (Tx power and OFDM modulation order) on ED performance of OFDM signals impacted by NU. Additionally, the obtained results offer further insight regarding the impact of the number of samples, SNR levels and the probability of a false alarm on ED probability of OFDM signals transmitted by means of different OFDM system designs. Such an overview of NU impact on ED performance presented for different OFDM system designs can serve as a reference to improve ED as a broadly accepted spectrum-sensing approach.

3. Contemporary OFDM system designs and modulations

3.1. OFDM system design

OFDM is a multicarrier transmission scheme. The main idea behind it is to transmit signals using a number of subcarriers orthogonal to each other [16]. The total bandwidth in OFDM systems is divided in a number of smaller bandwidths by spreading the transmitted signal over a number of subcarriers. Three types of algorithms (design options) are used by OFDM systems for signal transmission. The first design option is based on the so-called margin-adaptive (MA) algorithms which strive to minimize the Tx power subject to the data rate and BER constraints. In order to maintain the same transmission rate (i.e. keep the constellation order M unchanged) at the same QoS (i.e. same BER), the Tx power should be adjusted according to the channel condition: lower Tx power when the channel quality is good and vice versa [44]. Assuming OFDM system with a set of subcarriers *S= {1, ..., s, ..., L}*, such optimization problem can be modeled as

$$\underset{p_s}{Minimize}\ P_T = \sum_{s=1}^{L} p_s \tag{1}$$

Subject to:

$$BER_{av} = \frac{\sum_{s=1}^{L} b_s BER_s}{\sum_{s=1}^{L} b_s} \le BER_{th} \tag{2}$$

$$\sum_{s=1}^{L} p_s \le P_{th} \tag{3}$$

$$\sum_{s=1}^{L} b_s = const. \le b_{th} \tag{4}$$

where p_{s}, BER_s and b_s are the Tx power, BER and bit rate of *s-th* subcarrier, respectively. At any moment, the optimal selection of the total instantaneous Tx power (P_T) and consequently subcarriers Tx power must ensure that: average BER (BER_{av}) is below the predefined BER threshold BER_{th} (constraint 2), the sum of all Tx powers of each subcarrier (p_s) is below the overall Tx power threshold P_{th} (constraint 3) and the sum of L subcarrier bit rates (b_s) is constant and below the overall bit rate threshold b_{th} (constraint 4).

The second design option is based on the so-called rate-adaptive (RA) algorithms which aim to maximize the instantaneous data rate (b_T) subject to the Tx power and BER constraints. If the Tx power is kept unchanged, in order to maintain the same QoS (i.e. same BER), the transmitter needs to adapt the OFDM modulation scheme according to the channel condition. A higher constellation order (larger M) of OFDM modulation will be used (which also means a higher transmission rate) when the channel quality is good and vice versa. Many practical OFDM systems operate with constant Tx power since an approach based on adaptive modulation selection is easier for practical circuit design implementation [44]. Examples of such OFDM systems are WLAN, WiMAX, etc. However, to enable adaptive modulation, the information about the channel quality, usually measured at the receiver needs to be sent back to the transmitter on a reverse channel. The RA system design can be modeled as

Table 1. Key features of some common OFDM-based systems [45-48]

OFDM Parameter	DAB/EUREKA /DAB +	DVB-T	DVB-H	IEEE 802.11 n/ac/ah	IEEE 802.15.3a
Channel Bandwidth [MHz]	1.712	6, 7, 8	5, 6, 7, 8	802.11 n: 20 – 40 802.11 ac: 20 -160 802.11 ah: 1-16	3,100 – 10,600
Modulation scheme	π⁄4-DQPSK	QPSK, 16QAM, 64QAM	QPSK, 16QAM 64QAM	BPSK, QPSK, 16 QAM, 64 QAM, 256 QAM	TFI –OFDM (with 128 – point FT size), QPSK
Guard Interval [μs]	24.6 (all modes)	1/4, 1/8, 1/16, 1/32	1/4, 1⁄8, 1⁄16, 1⁄32	1/4, 1/8, 1/16 (IEEE 802.11 n/ac) 802.11n: 64, 128	0,00947
FFT size (k=1024)	Mode I: 2k Mode II: 512 Mode III: 256 Mode IV: 1k	2k, 8k	2k, 4k, 8k	802.11ac: 64, 128, 256, 512 802.11 ah: 32, 64, 128, 256, 512	64, 128, 256

Table 2. Key features of some common OFDMA-based systems [49-52]

OFDM Parameter	LTE	WiMAX	IEEE 802.20
Channel bandwidth [MHz]	1.4, 3, 5, 10, 15, 20	1.25 - 28	5, 10, 20
Modulation scheme	QPSK, 16 QAM, 64 QAM	BPSK, QPSK, 16 QAM, 64 QAM	QPSK, 8 PSK, 16 QAM, 64 QAM
Guard interval [μs]	1/4, 1/8, 1/16, 1/32	1/4, 1/8, 1/16, 1/32	6.51, 13.02, 19.53, 26.04
FFT size (k=1024)	128, 256, 512, 1k, 1536, 2k	128, 256, 512, k, 2k	512, 1024, 2048

$$\underset{b_s}{Maximize}\ b_T = \sum_{s=1}^{L} b_s \tag{5}$$

Subject to

$$BER_{av} = \frac{\sum_{s=1}^{L} b_s BER_s}{\sum_{s=1}^{L} b_s} \le BER_{th} \tag{6}$$

$$\sum_{s=1}^{L} p_s = const. < P_{th} \tag{7}$$

$$\sum_{s=1}^{L} b_s \le b_{th} \tag{8}$$

where the average BER (BER_{av}) must be below the predefined BER threshold BER_{th} (constraint 6), the sum of all Tx powers of each subcarrier must be constant and below the overall Tx power threshold P_{th} (constraint 7) and the sum of L subcarrier bit rates must be below the overall bit rate threshold b_{th} (constraint 8).

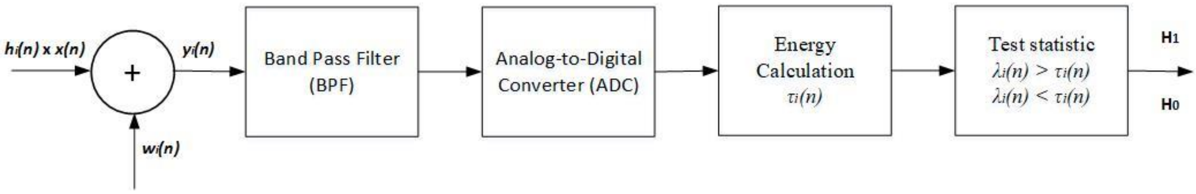


Figure 1. Block diagram of the energy detection technique

The third OFDM system design option is based on the contemporary bit and power loading (RA and MA) algorithms which strive to maximize the data rate and minimize the Tx power subject to the BER constraints in the channel. A motivation to jointly consider the rate and margin optimization problems can be found in the emerging wireless communication systems which operate under different requirements and diverse conditions. More specifically, power minimization is crucial when operating near other frequency-adjacent users or in interference-prone shared spectrum environments. Additionally, if there are enough guard bands to separate users, throughput maximization can be done for better channel utilization. The contemporary bit and power loading OFDM system design can be modeled as follows

$$\underset{p_s}{Minimize}\ P_T = \sum_{s=1}^{L} p_s \text{ and } \underset{b_s}{Maximize}\ b_T = \sum_{s=1}^{L} b_s \tag{9}$$

Subject to

$$BER_{av} = \frac{\sum_{s=1}^{L} b_s BER_s}{\sum_{s=1}^{L} b_s} \leq BER_{th} \tag{10}$$

$$\sum_{s=1}^{L} p_s \leq P_{th} \tag{11}$$

$$\sum_{s=1}^{L} b_s \leq b_{th} \tag{12}$$

where OFDM subcarrier Tx power and bit rate (modulation order) have been jointly optimized according to the channel conditions and must be below the predefined threshold values P_{th} and b_{th}, respectively.

3.2. OFDM modulations

OFDM is used in many telecommunication systems such as a Worldwide Interoperability for Microwave Access (WiMAX), IEEE 802.11a/g/n/ac/ad WLAN, Long-Term Evolution (LTE), LTE Advanced (LTE - A), Light Fidelity (Li-Fi), modern narrow and broadband power line communications (PLC) and it will be baseline technology to be used for the upcoming 5th generation (5G) networks. Also, OFDM has been adopted or proposed for several applications such as Asymmetric Digital Subscriber Line (ADSL), Digital Audio Broadcasting (DAB), Digital Video Broadcasting – Handheld/ Terrestrial (DVB-H/T) and Digital Terrestrial Multimedia Broadcast (DTMB) [5, 53-57]. Table 1 shows the key features of some OFDM-based communication technologies.

In addition to the OFDM technique, the OFDM access (OFDMA) technique is also used in practice. OFDMA is a version of OFDM modulation that happens to be optimized for multiple users, specifically for cell phones and other mobiles devices in cellular access networks. In OFDM users are allocated on the time domain scale only, while when using an OFDMA system, the user would be allocated by both, time and frequency. In OFDM, all sub-carriers of the symbol are used for providing data to a specific user. In OFDMA, the sub-carriers of each symbol may be divided among multiple users, thus enabling better use of the radio resources. OFDMA's dynamic allocation enables better use of the channel for multiple low-rate users and for the avoidance the narrowband fading and interference. OFDMA is used in IEEE 802.16 (WiMAX), IEEE 802.20 (iBurst) and LTE systems. OFDMA is also a candidate access method for the IEEE 802.22 Wireless Regional Area Networks (WRAN). Table 2 presents some of the key features of OFDMA-based systems.

From Table 1 and 2 it can be noticed that QPSK, 16 QAM, and 64 QAM are the most frequent modulation schemes used in contemporary OFDM-based communication technologies. For that reason, these modulation schemes have been selected in this work for performance analyses of the ED technique impacted by NU. However, the results obtained can be generalized for other OFDM modulation techniques.

Table 3. Parameters with corresponding descriptions

Parameter	Description
H_0	The hypothesis which determines the absence of the PU signal
H_1	The hypothesis which determines the presence of the PU signal
$y_i(n)$	The average signal received for *i-th* SU and for *n-th* sample
$w_i(n)$	AWGN signal for *i*-th SU during *n-th* sample
$\sigma_{n_i}^2$	The variance of AWGN for *i*-th SU without NU impact
$\sigma_{nu_i}^2$	The variance of AWGN for *i*-th SU with NU impact
$\sigma_{NU_i}^2$	The variance range of AWGN for *i*-th SU with NU impact
$h_i(n)$	Amplitude gain of the channel at the moment of the *n-th* sample
$x(n)$	Signal transmitted from PU during the *n-th* sample
τ_i	Energy test statistic signal for *i*-th SU
λ_i	The decision threshold signal level in the case of no noise uncertainty for *i*-th SU
λ_{di}	Probability detection threshold in the case of no NU
λ_{fai}	False alarm threshold in case of no NU
$\mathrm{P_{d_i}}$	The probability of detection in case of no NU
$\mathrm{P_{fa_i}}$	The probability of false alarm in case of no NU
$\mathrm{P_{m_i}}$	The probability of misdetection in case of no NU
$\mathrm{P_{d_i}^{NU}}$	The probability of energy detection with NU
$\mathrm{P_{fa_i}^{NU}}$	The probability of false alarm with NU
ρ	NU factor
Q	Standard Gaussian complementary cumulative distribution function (CDF)
Q^{-1}	Inverse standard Gaussian Complementary CDF
P	Average Tx signal power of PU
N	Total number of samples during sensing time without NU
$\mathrm{N^{NU}}$	Total number of samples during sensing time for NU
λ_{di}^{NU}	Probability detection threshold in case of NU
$\lambda_{fa_i}^{NU}$	False alarm threshold in case of NU
SNR	Signal to Noise Ratio at the position of SU

4. Spectrum sensing in the cognitive radio network

Spectrum sensing is the basic and essential mechanism of cognitive radio to find the unused spectrum. In this section, an overview of ED-based spectrum sensing and cognitive radio architecture are presented.

4.1. The energy detection model

As the main process of cognitive radio, spectrum sensing enables unlicensed users to adapt to the environment by detecting unused spectrum portions without causing interference to the licensed network. In order to sense the radio frequency environment, cognitive radio (SU) takes signal samples and then performs digital signal processing operations that produce average received signal energy known as test statistics. In order to simplify problem formulation, signals used in these analyses are assumed to be real-valued, however, the analysis can be easily extended to complex signals. For CRN with single PU and multiple SU where noise received at the position of SU is assumed to be additive white Gaussian noise (AWGN), the spectrum-sensing problem can be represented as a binary hypothesis, mathematically expressed by [9, 58, 59]:

$$\begin{aligned} H_0&: y_i(n) = w_i(n),\ i = 1, \ldots, \mathrm{M},\ n = 1, \ldots, \mathrm{N} \text{ if PU is absent} \\ H_1&: y_i(n) = h_i(n) \times x(n) + w_i(n),\ i = 1, \ldots, \mathrm{M},\ n = 1, \ldots, \mathrm{N} \text{ if PU is present} \end{aligned} \tag{13}$$

where $y_i(n)$ is the received signal by *i-th* SU during the *n-th* sample, $w_i(n)$ is the AWGN signal received by *i-th* SU with zero mean and variance $\sigma_{n_i}^2$ ($w_i(\mathrm{n}) \in \mathcal{N}(0, \sigma_{n_i}^2)$), $x(n)$ is a signal transmitted from PU during the *n-th* sample, $h_i(n)$ is random linear time-varying operator representing channel fading for the *i-th* SU at the moment of discrete time sample *n,* N is the total number of samples during sensing time and M is a total number of SUs [9]. It is assumed that all random processes are ergodic and stationary. In the analyses, it is also assumed that the primary signal *x(n)* is independent of the AWGN and fading. Since the spectrum-sensing time period is shorter than the transmission time period, it can be assumed that $h_i(n)$ is a constant in the theoretical analyses and consequently in computer simulations. Table 3 lists all the parameters used in this work with corresponding descriptions.

The presence or absence of a PU is usually defined by the statistical probability of PU signal detection. In order to evaluate ED performance, a decision threshold signal level (λ_i) is set and compared to the energy test statistic signal level obtained (τ_i) at the position of SU. The detection rule is defined by:

$$\begin{aligned} &\tau_i > \lambda_i, \text{ PU present} \\ &\tau_i < \lambda_i, \text{ PU absent} \end{aligned} \tag{14}$$

where the test statistic signal level (τ_i) is gained calculating the average received signal energy. Hence, for conventional ED, the average received signal energy for N samples is defined as the test statistic τ_i [60]:

$$\tau_i = \frac{1}{\mathrm{N}} \sum_{n=1}^{\mathrm{N}} |y_i(n)|^2 \tag{15}$$

The test statistic signal level is then compared to a predetermined threshold (λ_i) for i-th SU. The threshold (λ_i) is determined from the energy of noise. The accuracy of the threshold is key to the performance of the energy detector. In further analyses, the threshold value is assumed to be fixed and selected based on the known noise level. The hypothesis H_0 in relation (13) is validated if the energy of the received signal is lower than the signal threshold (14), thus signifying the presence of a spectrum hole. According to relation (13), the alternate hypothesis H_1 is validated if the received signal's energy at the SU cognitive radio is greater than the set threshold (14), which results in the conclusion that the PU is present [7, 32, 61].

Figure 1 shows the stages of the ED process performed by SU. The first process in the ED method is passing the received signal through the Band Pass Filter (BPF) to select an appropriate signal bandwidth [32]. Using the Analog to Digital Converters (ADCs), the analog signal is sampled to obtain a discrete signal. The digital output is squared, and to obtain the energy test statistic, the average of N samples is calculated based on relation (15). The average energy (test statistics) calculated is compared with the decision threshold (14). To determine the presence or absence of the PU signal, established binary hypotheses H_0 and H_1 presented with relation (13) are used.

In essence, the performance of ED technique is based on examining the Neyman-Pearson hypotheses. In order to test these hypotheses, the comparison between the log-likelihood ratio of the received signal and the decision threshold will be [7]:

$$H_1: log\left(\frac{P\left(y_0, y_{1,\dots\dots\dots\dots,} y_{(\mathrm{N}-1)} \middle|\, H_1\right)}{P\left(y_0, y_{1,\dots\dots\dots\dots,} y_{(\mathrm{N}-1)} \middle|\, H_0\right)}\right) > \lambda_i \tag{16}$$

$$H_0: log\left(\frac{P\left(y_0, y_{1,\dots\dots\dots\dots,} y_{(\mathrm{N}-1)} \middle|\, H_1\right)}{P\left(y_0, y_{1,\dots\dots\dots\dots,} y_{(\mathrm{N}-1)} \middle|\, H_0\right)}\right) < \lambda_i \tag{17}$$

where $P(y|\, H_0)$ and $P(y|\, H_1)$ represent the probability density functions (PDFs) of the null hypothesis H_0 and alternative hypothesis H_1.

Non-central chi-squared distribution with N degrees of freedom is used for expressing the presence of the PU signal ($\tau_i(n) > \lambda_i$). In the case of PU signal absence ($\tau_i(n) < \lambda_i$), central chi-squared distribution with N degrees of freedom is used, where N represents a number of samples used in the ED process. When the ED observation interval (N) is large enough, the PDF of the received signal can be approximated as Gaussian distribution, where $f\,(\tau_i(n))$ is PDF of $\tau_i(n)$. If the noise variance is known and there is no NU, the central limit theorem gives the following approximations of the test statistics PDF [58, 61]:

$$f\,(\boldsymbol{\tau_i(n)}) \sim \mathcal{N}\,(\boldsymbol{\sigma^2_{n_i}}, \tfrac{\boldsymbol{2}}{\boldsymbol{N}}\boldsymbol{\sigma^4_{n_i}})\ \text{(under } \boldsymbol{H_0})$$

$$f\,(\boldsymbol{\tau_i(n)}) \sim \mathcal{N}\,(\boldsymbol{P} + \boldsymbol{\sigma^2_{n_i}}, \tfrac{\boldsymbol{2}}{\boldsymbol{N}}(\boldsymbol{P} + \boldsymbol{\sigma^2_{n_i}})^2)\ \text{(under } \boldsymbol{H_1}) \tag{18}$$

where $P = \sum_{n=1}^{\mathrm{N}} \frac{|x(n)|^2}{\mathrm{N}}$ is the average signal power of PU and σ_n^2 is noise variance. The probability of detection ($\mathrm{P_{d_i}}$) and the probability of a false alarm ($\mathrm{P_{fa_i}}$) can be expressed as [58, 60, 61]

$$\mathrm{P_{d_i}} = Q\left(\frac{\lambda_{di} - (\mathrm{P} + \sigma^2_{n_i})}{\sqrt{\frac{2}{\mathrm{N}}}(P + \sigma^2_{n_i})}\right) \tag{19}$$

$$\mathrm{P_{fa_i}} = Q\left(\frac{\lambda_{fai} - \sigma^2_{n_i}}{\sqrt{\frac{2}{\mathrm{N}}}\sigma^2_{n_i}}\right) \tag{20}$$

respectively, where Q (.) is the standard Gaussian complementary cumulative distribution function (CDF) [60]. The probability of detection ($\mathrm{P_{d_i}}$) is the probability that the SU correctly declares that a PU is present, when the PU is really present. The probability of a false alarm ($\mathrm{P_{fa_i}}$) is the probability that SU incorrectly declares that a PU is present when the PU is actually absent. Both parameters are commonly used to express the efficiency of the ED process. In addition to those probabilities, the probability of misdetection ($\mathrm{P_{m_i}}$) presents the probability that PU is actually present while SU declares that it is absent. The misdetection probability ($\mathrm{P_{m_i}}$) for *i –th* SU can be written as:

$$\mathrm{P_{m_i}} = 1 - \mathrm{P_{d_i}} \tag{21}$$

And a lower probability of misdetection (or higher probability of detection) is favourable since it offers better chances for accurate detection of PU signal at the position of SU.

4.2. Spectrum-sensing model without noise uncertainty

Previous analyses of the spectrum-sensing model are based on the assumption that exact information about noise power is accurately known at the position of SU. This model excludes any fluctuations of noise also known as noise uncertainty (NU) during the ED process. A method based on an adaptive inverse cumulative density function (ICDF) is used in this work to determine the ED threshold for the spectrum-sensing model presented. This method is based on the adaptive and fixed thresholding approach. In the adaptive ICDF method, the threshold is a function of the probability of false alarm ($\mathrm{P_{fa_i}}$) [7]. Based on (19) and (20), for hypothesis H_1 and for a constant value of the probability of detection ($\mathrm{P_{d_i}}$), the probability detection threshold (λ_{di}) for the ED process without NU is derived as [58, 60, 61]:

$$\lambda_{di} = Q^{-1}(\mathrm{P_{d_i}})(P + \sigma^2_{n_i})\sqrt{\frac{2}{\mathrm{N}}} + (P + \sigma^2_{n_i}) \tag{22}$$

where Q^{-1} (.) is the inverse standard Gaussian Complementary CDF. For a fixed $\mathrm{P_{fa_i}}$ value, the false alarm threshold (λ_{fai}) for the case without NU is given by [59-61]:

$$\lambda_{fai} = Q^{-1}(\mathrm{P_{fa_i}})\sigma^2_{n_i}\sqrt{\frac{2}{\mathrm{N}}} + \sigma^2_{n_i} \tag{23}$$

Equations (22) and (23) indicate that threshold estimation depends on the noise variance ($\sigma^2_{n_i}$), the average PU signal power *(P)*, the number of the samples (N) and the required detection ($\mathrm{P_{d_i}}$*)* or false alarm probability ($\mathrm{P_{fa_i}}$).

Since SNR at the position of SU is impacted by average signal PU power and noise variance, SNR can be expressed as: SNR = $P/\sigma_{n_i}^2$.

Hence, a minimal overall number of samples (N) during ED sensing time for accurate PU detection can be expressed in terms of $\mathrm{P_{fa_i}}$, $\mathrm{P_{d_i}}$ and SNR [60, 61] as:

$$\mathrm{N} = \frac{2[Q^{-1}(\mathrm{P_{fa_i}}) - Q^{-1}(\mathrm{P_{d_i}})(1+\mathrm{SNR})]^2}{\mathrm{SNR}^2} \tag{24}$$

showing that signal detection could be achieved at arbitrarily low SNRs by increasing the sensing time (number of samples N) if perfect knowledge of noise power σ_n^2 exists. It can be noticed that the expression (24) is free from the decision threshold. Thus, a greater number of samples results in a higher probability of detection during the ED process, regardless of the threshold set. Relation (24) defines the minimum number of samples in the ED process in order to achieve ED for a specific combination of $\mathrm{P_{fa_i}}$, $\mathrm{P_{d_i}}$ and SNR. It is obvious that the performance will gradually improve as N increases. In addition, accurate PU detection probability can be obtained even if the SNR is lower, if N is large enough, and NU is absent. Therefore, a weak signal without NU can be detected by means of the ED technique, if an appropriate number of samples is used [29].

Interdependence between the $\mathrm{P_{d_i}}$ and $\mathrm{P_{fa_i}}$ is developed from relation (24), and it is expressed as

$$\mathrm{P_{d_i}} = Q\left(\frac{Q^{-1}(\mathrm{P_{fa_i}}) - \sqrt{\frac{\mathrm{N}}{2}}\,\mathrm{SNR}}{1+\mathrm{SNR}}\right) \tag{25}$$

where the parameters having the main impact on PU signal detection are the probability of false alarm ($\mathrm{P_{fa_i}}$), SNR level and the number of samples (N).

5. Energy detection with noise uncertainty

The previous section presents the fundamental analyses of the ED technique. The analyses assumed that noise power detected by SU is exactly known. Mostly in practice, it is not possible to obtain exact information about noise power which changes randomly in space and time. For that reason, SU often experiences the uncertainty in the noise power estimation (detection) which is known as NU [29, 61]. Assuming the NU does not exist poses a limitation on the ED performance of the given cognitive radio system. Hence, not taking noise power uncertainty into account means avoiding realistic conditions in the network. To have a more realistic performance estimate, the ED system model is extended by taking into account the NU impact on the overall ED process. Hence, in this section, a derived mathematical model is provided to show the influence of the NU on ED system performance.

5.1. Spectrum-sensing model with noise uncertainty

NU is the result of noise power fluctuation. Fluctuation in noise power causes a drop in the quality of sensing sensitivity. As a consequence of this phenomena, the detection accuracy drops quickly which can result in a wrong decision of SU and entry of SU in transmission state causing SU interference to the PU [61]. NU imposes a limit on the capability of detecting weak signals. Energy detector performance cannot be improved by increasing the sensitivity when the SNR of PU signals is below a certain level known as SNR-wall ($\mathrm{SNR_{wall}}$). Below the SNR-wall, no matter how much time the primary signal is observed, the energy detection becomes unreliable or even impossible [7].

In the case when NU impacts the ED process, AWGN power distribution is also assumed to be zero mean with variance $\sigma_{nu_i}^2$ ($w_i(\mathrm{n}) \in \mathcal{N}(0, \sigma_{nu_i}^2)$). Additionally, the impact of the noise power uncertainty can be expressed with NU factor ρ (ρ≥*1*). When factor ρ=1, there is no NU and there is no variation in the noise power. This case was defined in the previous section. A case where factor ρ>1 implies there is NU and higher values of

Table 4. Upper and lower noise variances, NU deviations and SNR walls for different test scenarios

Scenario No.	NU parameter	$\sigma^2_{lnu_i}$	$\sigma^2_{unu_i}$	Δ_{nu_i} (dB)	SNR_{wall}	$SNR_{wall}\ (dB)$
1.	$\sigma^2_{n_i}$= 1.00, ρ= 1.00	1.00	1.00	0	0	N/A
2.	$\sigma^2_{NU_i}$ = 1.01, ρ= 1.01	1.00	1.0201	0.04321	0,0199	-17.011
3.	$\sigma^2_{NU_i}$ = 1.01, ρ= 1.02	0.9901	1.0302	0.086	0.0396	-14.023
4.	$\sigma^2_{NU_i}$ = 1.01, ρ= 1.03	0.9805	1.0403	0.1283	0.05912	-12.2826
5.	$\sigma^2_{NU_i}$ = 1.01, ρ= 1.05	0.9619	1.0605	0.2118	0.0976	-10.105

ρ imply higher NU. For example, if NU factor is ρ =1.01, this means that the noise power fluctuations are in order of 1% of the received absolute noise power variance level $\sigma^2_{nu_i}$.

Hence, the limits of noise variance ($\sigma^2_{NU_i}$) of AWGN impacted with NU can be expressed in a single interval $\sigma^2_{NU_i}\,\epsilon[{}^{\sigma^2_{nu_i}}\!/\!_{\rho}\,, \rho\sigma^2_{nu_i}]$. For that reason the $\sigma^2_{n_i}$ in (19) and (20) would be replaced by these limiting values and the expressions for the probability of detection $(\mathrm{P_{d_i}})$ and the probability of false alarm $(\mathrm{P_{fa_i}})$ for a scenario which includes NU are modified as [60, 61]:

$$\mathrm{P^{NU}_{d_i}} = \min_{\sigma^2_{NU_i}\epsilon[{}^{\sigma^2_{nu_i}}/_{\rho},\rho\sigma^2_{nu_i}].} Q\left(\frac{\lambda_i-(P+\sigma^2_{NU_i})}{\sqrt{\frac{2}{\mathrm{N^{NU}}}}(P+\sigma^2_{NU_i})}\right) = \mathrm{Q}\left(\frac{\lambda^{NU}_{d_i}-(P+\frac{\sigma^2_{nu_i}}{\rho})}{\sqrt{\frac{2}{\mathrm{N^{NU}}}}(P+\frac{\sigma^2_{nu_i}}{\rho})}\right) \tag{26}$$

$$\mathrm{P^{NU}_{fa_i}} = \max_{\sigma^2_{NU_i}\epsilon[{}^{\sigma^2_{nu_i}}/_{\rho},\rho\sigma^2_{nu_i}].} Q\left(\frac{\lambda_i-\sigma^2_{NU_i}}{\sqrt{\frac{2}{\mathrm{N^{NU}}}}\sigma^2_{NU_i}}\right) = \mathrm{Q}\left(\frac{\lambda^{NU}_{fa_i}-\rho\sigma^2_{nu_i}}{\sqrt{\frac{2}{\mathrm{N^{NU}}}}\rho\sigma^2_{nu_i}}\right) \tag{27}$$

In relations (26) and (27), $P^{NU}_{d_i}$ represents the probability of PU energy detection, while $P^{NU}_{fa_i}$ represents the probability of false alarm for the case of reception of PU signal impacted by NU. Besides the Tx power of PU signal (*P*), the number of samples (*N*) and variance impacted with NU ($\rho, \sigma^2_{NU_i}$), relations (26) and (27) indicate that the probability of detection threshold λ^{NU}_{di} and the probability of false alarm threshold $\lambda^{NU}_{fa_i}$ affect $P^{NU}_{d_i}$ and $P^{NU}_{fa_i}$, respectively.

For a constant value of $P^{NU}_{d_i}$, the probability of detection threshold in case of NU (λ^{NU}_{di}) can be derived from (26) and expressed as:

$$\lambda^{NU}_{di} = Q^{-1}\left(\mathrm{P^{NU}_{d_i}}\right)\left(P+\frac{\sigma^2_{nu_i}}{\rho}\right)\sqrt{\frac{2}{\mathrm{N^{NU}}}} + \left(P+\sigma^2_{nu_i}/\rho\right) \tag{28}$$

Similarly, the probability of the false alarm threshold in case of NU for a constant value of $\mathrm{P^{NU}_{fa_i}}$ can be derived from (27) and expressed as:

$$\lambda^{NU}_{fai} = Q^{-1}(\mathrm{P^{NU}_{fa_i}})\sigma^2_{nu_i}\sqrt{\frac{2}{\mathrm{N^{NU}}}} + \sigma^2_{nu_i}\ \rho \tag{29}$$

A number of samples for performing ED when PU signal is impacted by NU [29] can be obtained by modifying equation (24) as follows:

$$\mathrm{N^{NU}} = \frac{2\left[\rho Q^{-1}\left(\mathrm{P^{NU}_{fa_i}}\right)-\left(\frac{1}{\rho}+\mathrm{SNR}\right)Q^{-1}\left(\mathrm{P^{NU}_{d_i}}\right)\right]^2}{\left[\mathrm{SNR}-\left(\frac{\rho^2-1}{\rho}\right)\right]^2} \tag{30}$$

where N^{NU} represents the minimal number of samples needed for an accurate detection of the PU signal in the presence of NU during the ED process. Relation (30) confirms that the energy detector cannot detect the signal if its power is less than $\frac{\rho^2-1}{\rho}$ of the uncertainty in the noise power, i.e. $P \leq \mathrm{SNR_{wall}} = \left(\frac{\rho^2-1}{\rho}\right)\sigma_{nu_i}^2$. Hence, if the noise has a slightly larger value than the signal, the presence of the signal is indistinguishable from the noise.

By scaling the NU factor, the impact of NU can be included in the calculation of the sampling number. For the case when ρ =1 and $\sigma_{n_i}^2 = \sigma_{nu_i}^2$, relations (30) and (24) become equal if $P_{d_i} = P_{d_i}^{NU}$ and $P_{fa_i} = P_{fa_i}^{NU}$. However, when ρ is larger (i.e. ρ>1.05) or $\sigma_{n_i}^2 \leq \sigma_{nu_i}^2$ and for low SNR values, to have accurate detection the number of samples must vastly increase ($N \to \infty$) what means that the detection duration must be extremely long. This is impossible to realize in practice, especially in the low SNR environment. In other words, cognitive performance is greatly influenced by the NU level (ρ), SNR and detection duration (N) [60]. For different values of the NU factor (ρ), the relation between P_{d_i} and $P_{d_i}^{NU}$ is expressed as: $P_{d_i} = P_{d_i}^{NU}$ if $N = N^{NU}, \sigma_{n_i}^2 = \sigma_{nu_i}^2$ and $\rho = 1.00$ or $P_{d_i} > P_{d_i}^{NU}$ if $N = N^{NU}, \sigma_{n_i}^2 \leq \sigma_{nu_i}^2$ and $\rho > 1.00$. Hence, when there is no NU (ρ = 1.00 and $\sigma_{n_i}^2 = \sigma_{nu_i}^2$), the probabilities P_{d_i} and $P_{d_i}^{NU}$ are the same. When ρ >1.00 and/or $\sigma_{n_i}^2 \leq \sigma_{nu_i}^2$, the probability of detection P_{d_i} and $P_{d_i}^{NU}$ differ since NU impacts the probability of energy detection $P_{d_i}^{NU}$.

The interdependence between $P_{d_i}^{NU}$ and $P_{fa_i}^{NU}$ is derived from (30), and can be expressed as:

$$P_{d_i}^{NU} = Q\left(\frac{\rho Q^{-1}\left(P_{fa_i}^{NU}\right) - \left(\mathrm{SNR} - \frac{\rho-1}{\rho}\right)\sqrt{\frac{N^{NU}}{2}}}{\frac{1}{\rho}+\mathrm{SNR}}\right) \tag{31}$$

Unlike relation (25), relation (31) takes into account NU through NU factor ρ which enables (in relation (31)) modeling of NU impact on the probability of detection.

5.2 Estimation of noise uncertainty

The introduction part of Section 5 emphasized that the noise power level may vary over time which causes the NU problem. The NU can be categorized into two types: environmental and receiver device NU. The environmental NU component is caused by intentional or unintentional transmissions of neighbour users. Time-varying thermal noise in receiver components and the nonlinearity of receiver components cause the NU at the receiver device [62]. Although the receiver device NU component is slower in variations than the environmental NU component, in practice, it is very difficult to obtain an accurate noise power which must be estimated. In this analysis, NU estimation is based on the distribution of the uncertainty of the noise power within the interval $\sigma_{NU_i}^2 \epsilon \left[\sigma_{lnu_i}^2 = \sigma_{nu_i}^2/\rho, \sigma_{unu_i}^2 = \rho\sigma_{nu_i}^2\right]$, where the lower and upper bounds of the NU variance interval are given as

$$\sigma_{lnu_i}^2 = \sigma_{nu_i}^2 \cdot 10^{(-\Delta_{nui}/10)} = \frac{1}{\rho} \cdot \sigma_{nu_i}^2 \tag{32}$$

$$\sigma_{unu_i}^2 = \sigma_{nu_i}^2 \cdot 10^{(+\Delta_{nui}/10)} = \rho \cdot \sigma_{nu_i}^2 \tag{33}$$

and Δ_{nui}=10$\log_{10}$ρ corresponds to the deviation of noise variance around nominal value ($\sigma_{nu_i}^2$) expressed in dB for *i-th* SU. This NU model is further used in the analyses to quantify the impact of NU on the performance of the ED process. The upper bound on ρ is defined as $+\Delta_{nui}=\sup\{10\log_{10}\rho\}$, where $+\Delta_{nui}$ represents upper NU bound of the uniformly distributed interval [$-\Delta_{nui}$, $+\Delta_{nui}$] and $-\Delta_{nui}=\inf\{10\log_{10}(\frac{1}{\rho})\}$ represents the lower NU bound. If no environmental NU is assumed, the NU deviation of a receiving device in practice is generally less than ±1 dB (e.g. [−1 dB, 1 dB]) [62, 63]. However, in practice, the environmental NU caused by the interference

Algorithm 1: Generation of OFDM signals

```
Input 1: modulation order m (QPSK, 16 QAM, 64 QAM), number of samples (N), size of each ofdm block (block_size), points for the FFT/IFFT (no_of_fft_points/ no_of_ifft_points), length of cyclic prefix (cp_len), reference constellation (refconst), normalization type (type) and target power (power)
Output: OFDM signal (ofdm_signal)
Initialize: OFDM signal
    Step 1: Generate vector of random data points for M-PSK or M-QAM modulation
        data_source= randsrc(1, N, 0:m-1);
        qpsk(qam)_modulated_data = psk(qam)mod(data_source, m);
        normfactor = modnorm(refconst,type,power);
        Tx= normfactor*psk(qam)mod(data_source, m);
    Step 2: Perform IFFT on each block
            num_cols=length(qpsk(qam)_modulated_data)/block_size;
            data_matrix = reshape(Tx, block_size, num_cols);
            cp_start = block_size-cp_len;
            cp_end = block_size;
            for i=1:num_cols,
            ifft_data_matrix(:,i) = ifft((data_matrix(:,i)),no_of_ifft_points);
    Step 3: Compute Cyclic Prefix and append it to the actual OFDM block
         for j=1:cp_len,
            actual_cp(j,i) = ifft_data_matrix(j+cp_start,i);
end
         ifft_data(:,i) = vertcat(actual_cp(:,i),ifft_data_matrix(:,i));
  end
    Step 4: Convert to serial stream for transmission
        [rows_ifft_data cols_ifft_data]=size(ifft_data);
        len_ofdm_data = rows_ifft_data*cols_ifft_data;
    Step 5: Actual OFDM signal to be transmitted
        ofdm_signal = reshape(ifft_data, 1, len_ofdm_data);
```

of neighboring users can contribute to a significant increase in NU bound and deviation.

In order to analyze the ED of different OFDM system designs under such an NU model, five different test scenarios presented in Table 4 are taken into consideration. The test scenarios are based on different combinations of nominal noise variances ($\sigma_{n_i}^2$ or $\sigma_{NU_i}^2$) and NU factors ($\rho = 1.0, 1.01, 1.02, 1.03, 1.05$). In order to have test scenarios that are as realistic as possible, two different nominal noise variances are selected ($\sigma_{n_i}^2, \sigma_{nu_i}^2$), each corresponding to a practical scenario characterising the absence or presence of NU, respectively. Also, the NU factors selected for the analyses (Table 4) correspond to realistic noise variance deviations characteristic for OFDM communication systems lacking a strong impact of environmental NU. For a specific test scenario, theoretical SNR_{wall} in real ($\text{SNR}_{\text{wall}} = \left(\frac{\rho^2-1}{\rho}\right)\sigma_{nu_i}^2$) and logarithmic ($\text{SNR}_{\text{wall}}(dB) = 10\log_{10}\text{SNR}_{\text{wall}}$) scale are also presented in Table 4, showing the values characteristic to the ED method.

Algorithm 2: Simulation of the ED process

1: Input 1: OFDM signal (ofdm_signal), len_ofdm_data, number of samples (N), SNR, NU factor (ρ), noise variance ($\sigma_{n_i}^2$), length of $\mathrm{P}_{\mathrm{fa_i}}$ and the number of Monte Carlo simulations (kk)

3: Output: Probability of detection ($\mathrm{P}_{\mathrm{d_i}}$)

4: On initialized OFDM signal (ofdm_signal) do:

Repeat

Step 1: Simulation Probability of Detection vs. Probability of False Alarm

5: set kk = number of Monte Carlo simulations

6: set Pfa=probability of false alarm

7: **for** p = 1:length($\mathrm{P}_{\mathrm{fa_i}}$);

8: i1=0; i2=0;

9: **for** kk=1:10000;

Step 2: Generate AWGN noise with zero mean and variance

10: Noise_1 (ρ=1.00)= sqrt($\sigma_{n_i}^2$).*randn (1, len_ofdm_data);

11: Noise_2 (ρ>1.00)= sqrt($\sigma_{nu_i}^2$).*randn (1, len_ofdm_data);

Step 3: Generate PU signal and Received signal with noise calculation

12: final_ofdm_signal = sqrt(SNR).*ofdm_signal;

13: received_signal_1 = final_ofdm_signal + Noise_1;

14: received_signal_2 = final_ofdm_signal + Noise_2

Step 4: Received signal energy calculation

15: energy_calc_1 = abs(received_signal_1).^2;

16: energy_calc_2 = abs(received_signal_2).^2;

Step 5: Test statistic calculation using (15)

17: test_stat_1 =(1/N).*sum(energy_calc_1);

18: test_stat_2 =(1/N).*sum(energy_calc_2);

Step 6: Threshold evaluation using (23) and (29)

19: thresh1(p) = (qfuncinv(P_{fa_i}(p))./sqrt(N))+ 1;

20: thresh2(p) = (qfuncinv(P_{fa_i}(p)).* ρ./sqrt(N))+ ρ;

Step 7: Decision making using (14)

21: **if** (test_stat_1 >= thresh1(p));

22: i1 = i1+1;

23: **end**

24: **if** (test_stat_2 >= thresh2(p));

25: i2 = i2 + 1;

26: **end**

27: **end**

Step 8: Monte Carlo simulation to determine Pdi using (13)

28: $\mathrm{P}_{\mathrm{d_i}}$1(p) = i/kk;

29: $\mathrm{P}_{\mathrm{d_i}}$2(p) = i2/kk;

30: **end**

31: **Until** $\mathrm{P}_{\mathrm{d_i}}$= [0, 1]

Table 5. Simulation parameters

Parameter	Value/Type
PU signal	OFDM
Modulation type	QPSK, 16 QAM and 64 QAM
Channel noise type	AWGN
Number of samples/FFT size (samples)	128, 256, 512, 1024
SNR ratio (dB)	-25 to 10
The probability of detection/false alarm	[0, 1]
Number of Monte-Carlo iterations	10,000
Noise variance $\sigma_{n_i}^2$ for signals without NU (ρ=1.00)	1.00
Noise variance $\sigma_{nu_i}^2$ for signals with NU (ρ>1.00)	1.01
NU factor ρ	1.00, 1.01, 1.02, 1.03, 1.05

6. The Energy Detection Algorithms

Algorithms for simulating spectrum sensing based on the ED concept are developed and presented in this section. To model the spectrum sensing algorithm, the MATLAB software is used. This approach is selected because it represents an appropriate statistical analysis tool which can be applied to simulate the ED process [8, 64]. In order to model the impact of NU on the ED process of the OFDM signals, Algorithm 1 and Algorithm 2 have been developed.

Based on Algorithm 1, different OFDM modulated signals have been generated. The first line of Algorithm 1 presents the setup of input parameters used for the generation of OFDM signals. The values such as: modulation order m (QPSK, 16 QAM, 64 QAM), number of samples (N), size of each ofdm block (*block_size*), points for the Fast Fourier Transform FFT/ Inverse FFT (*no_of_fft_points/ no_of_ifft_points*), length of cyclic prefix (*cp_len*), reference constellation (*refconst*), normalization type (*type*) and target Tx power (*power*) are set. In lines 5-8, generating a vector of random data points for m-PSK or m-QAM modulation and setting the scaling factor for normalizing modulation Tx power output is performed. Lines 9-14 of Algorithm 1 present the generation of IFFT on each block of OFDM signal. From lines 15 to 19, Cyclic Prefix (CP) is computed and appended to the actual OFDM block. The generation of the OFDM signal (*ofdm_signal*) is modeled in lines 20-22 of Algorithm 1.

After generating the specific OFDM signal, Algorithm 2 is used for spectrum-sensing simulation of the PU signals in the ED process with and without NU impact. The first line of Algorithm 2 presents the setup of input parameters used for the simulation of the ED process. The values such as OFDM signal (*ofdm_signal*) generated by Algorithm 1, len_ofdm_data (presents length of OFDM data after parallel-to-serial conversion), SNR range, NU factor, noise variance ($\sigma_{n_i}^2$), length of the probability of false alarm (P_{fa_i}) and the number of Monte Carlo simulations (kk) are set. Monte-Carlo simulations are used to improve the accuracy of the simulation process. Hence, in lines 5 to 10 of Algorithm 2, the parameters for performing Monte-Carlo simulation, such as length of P_{fa_i} and a number of Monte Carlo simulations are set and executed.

Lines 11 to 12 show part of the pseudo-code for generating AWGN with zero mean and variance which differs for signals without ($\sigma_{n_i}^2 = 1.00$) and with NU impact ($\sigma_{nu_i}^2 = 1.01$). The variance of AWGN signal without NU ($\sigma_{n_i}^2 = 1.00$) is expressed with NU factor ρ =1.00, while the variance of AWGN noise with NU is set to a predefined level ($\sigma_{nu_i}^2 = 1.01$) with NU factor ρ >1. The AWGN signal is generated using a Matlab random number generator function (*randn*) in which all the samples follow Gaussian distribution.

In line 13, the final OFDM signal (*final_ofdm_signal*) is generated by multiplying the values of the OFDM signal and the linear values of SNR. Two types of received signal are shown in lines 14-15. The first one (*Received_signal_1*) presents a OFDM signal with a noise variance ($\sigma_{n_i}^2$) not impacted by NU, while the second one (*Received_signal_2*) presents a OFDM signal with a noise variance ($\sigma_{NU_i}^2$)impacted by NU.

Lines 16 – 17 of the Algorithm 2 show how the received signal energy for the case without and with NU impact, (*energy_calc_1* and *energy_calc_2,* respectively) is calculated.

In lines 18 – 19, the average signal received for N samples is defined as test statistics calculation for two cases: test statistics for signals without NU impact (*test_stat_1)* and for signals with NU impact (*test_stat_2)*. Calculating the averaged received signal is performed according to relation (15).

Lines 20 – 21 present threshold evaluations of the received signal. *Thresh1(p*) presents the first case where there is no NU (ρ =1.00), while *Thresh2(p)* presents the second case with NU. Mathematical expressions of the first and second cases are given with relations (23) and (29), respectively.

The decision-making process is presented in lines 22 - 27 of Algorithm 1. For each of the cases analyzed, the threshold comparison is made with corresponding test statistics: *test_stat_1* and *test_stat_2*. If the test statistic is higher or equal to the threshold, PU is present and hypothesis H_1 is validated as indicated in relation (13). If the test statistic is lower than the threshold, PU is absent and hypothesis H_0 is validated according to relation (13).

In lines 28 – 32, in order to determine the probability of PU signal detection $\mathrm{P_{d_i}}$, Monte Carlo iterations are used to get the most realistic results for all the cases analyzed.

7. Simulation Results

In this section, the parameters used in simulations and an overview of simulation results are presented. Spectrum sensing based on the ED technique at the location of SU is simulated for the three types of OFDM system designs (RA, MA and joint RA and MA OFDM systems). The differences among the PU signals received are simulated through the impact of NU on the received signal. This enables studying the impact of NU on ED capabilities of differently modulated OFDM signals.

7.1. Simulation Software and Parameters

Matlab simulation toolbox (version R2016a) was used to generate OFDM signal based on Algorithm 1 and to model the ED process based on Algorithm 2. Three types of OFDM modulations are used in the simulations: QPSK, 16 QAM and 64 QAM. Those modulation types are the most frequently used in practical OFDM-based systems, as shown in the analyses presented in Section 3.2. A summary of the parameter values used for the simulation of ED process for the OFDM system designs analysed is shown in Table 5. As indicated in Table 5, different FFT sizes (128, 256, 512 and 1024) of OFDM signals are used for analyses. The analyses are performed for SNR of received PU signals in the range between – 25 dB and 10 dB. It is reasonable to believe that the selected SNR range offers the possibility of signal detection in practical scenarios for many communication technologies which use the OFDM technique. The probabilities of signal detection ($\mathrm{P_{d_i}}$) and false alarm ($\mathrm{P_{fa_i}}$) are analyzed for the range between 0 and 100%. The results are obtained for 10,000 Monte Carlo simulations (Table 5). The selected numbers of Monte-Carlo simulations are based on the trade-off between simulation accuracy and the duration of the simulation. To model the impact of NU on the received OFDM signal during the ED process, different values of the NU factor are used (Tables 4 and 5). To exclude the impact of NU in the model, an NU factor ρ equal to 1 is used (Tables 4 and 5). To simulate the ED of a more realistic PU signal, the NU factors between 1.01 and 1.05 are used (Tables 4 and 5). The selection of such NU factors implies variations of noise between 1% and 5% of AWGN, which is common in practice.

The interdependence between the probability of PU signal detection ($\mathrm{P_{d_i}}$) and the false alarm probability ($\mathrm{P_{fa_i}}$) has been commonly expressed by means of receiver operating characteristic (ROC) curves [7, 33]. The ROC curve concept, as a useful approach in evaluating and comparing PU signal detection efficiency, is used in the next sections to present \the simulation results obtained.

7.2. The effect of noise uncertainty on the energy detection process

The influence of the NU on the ED of RA OFDM systems is studied first and the results are presented in Figure 2. The results were obtained for a fixed number of samples (N=128), fixed Tx power of PU and different levels of NU factors expressing the intensity impact of AWGN variations on the ED of OFDM signals. Figure 2 presents the results obtained in the form of the ROC curves for different values of SNRs and m-PSK/m-QAM constellation orders at the position of SU.

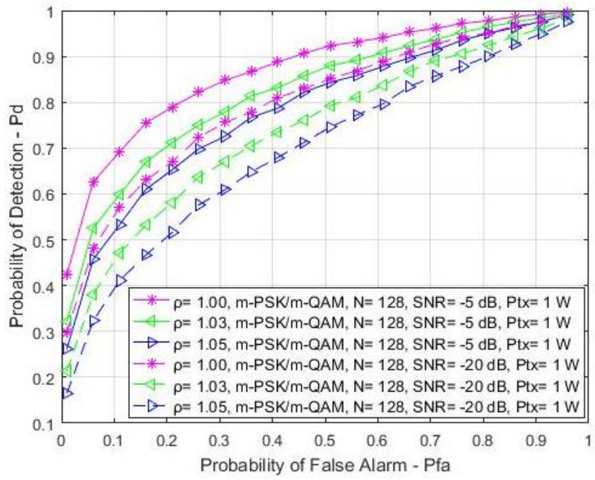


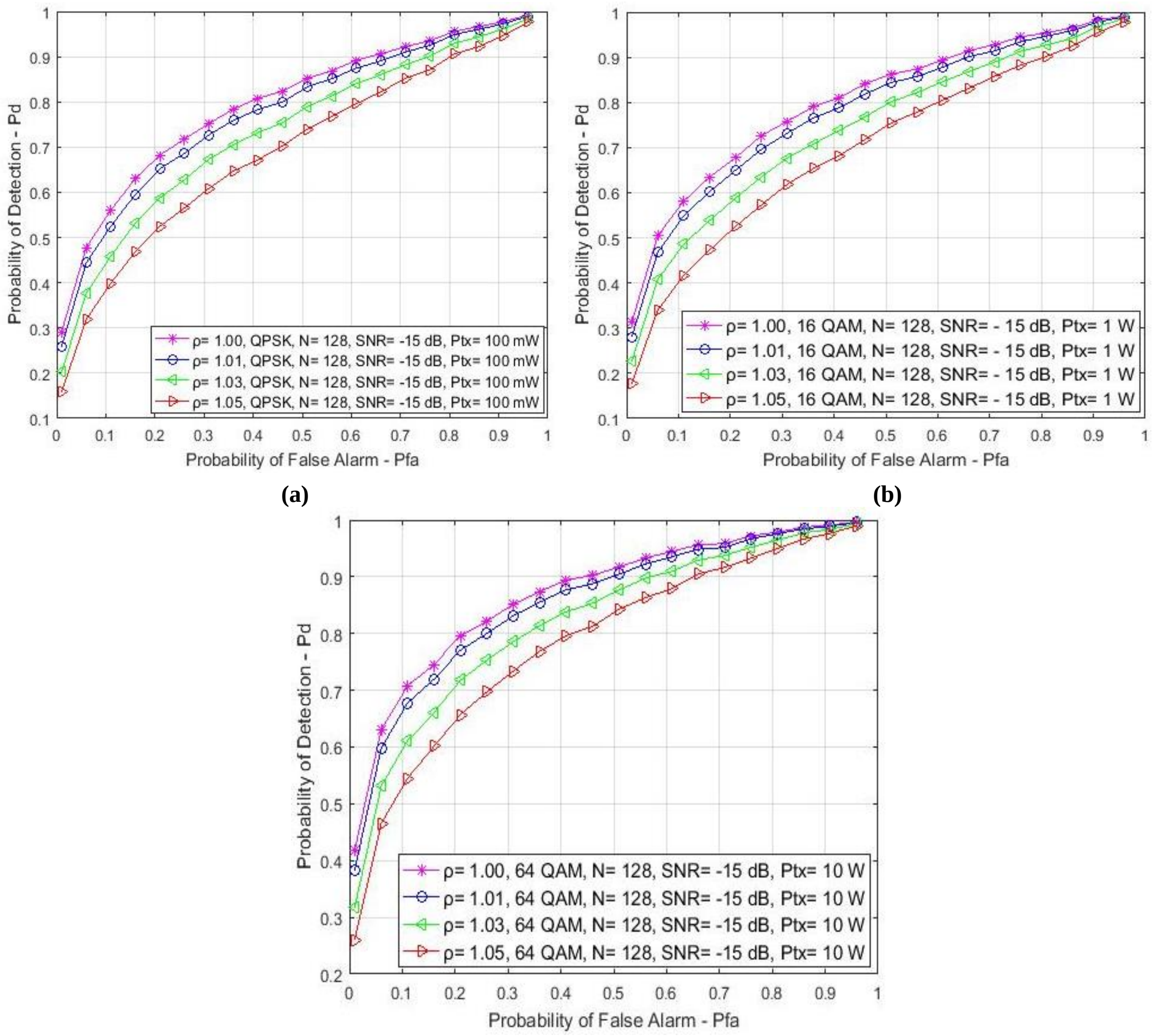
Figure 2. ROC curves for RA OFDM systems based on m-PSK/m-QAM modulations impacted by different values of NUs in the case of two different SNR levels

According to Figure 2, the probability of detection (P_{d_i}) is the same for any m-PSK or m-QAM modulation. This means that the probability of detection is independent of the modulation (constellation) order (m) for m-PSK or m-QAM OFDM systems transmitting with fixed Tx power (RA systems). This is because the PU in such systems always transmits with the same Tx power and the energy of the signal received during the ED process at the location of the SU can only be impacted by noise fluctuation. This is confirmed in Figure 2, indicating that for the same Tx power of PU, SNR and number of samples, higher noise variations have a negative impact on the probability of detection (P_{di}). Hence in RA OFDM systems, a dynamic adjustment of the modulation order during transmission with fixed Tx power does not have an impact on the probability of PU signal detection in ED OFDM systems.

Further analyses in terms of the impact of NU on ED of joint RA and MA OFDM based systems have been performed and presented in Figure 3. The results are obtained for a fixed number of samples (N=128), fixed SNR (min. -15 dB) at the position of SU and for the three most frequently used OFDM modulations: QPSK, 16-QAM and 64-QAM. Figure 3 presents the results obtained in the form of the ROC curves for different values of NU factors and different levels of PU Tx powers and corresponding modulations. The selected values of the Tx power are characteristic for OFDM-based commutation systems such as WLAN (100 mW) or 2G/3G/4G cellular mobile systems (1 W and 10 W).

According to Figures 3(a) – (c), for ED of signals impacted by an equal NU variation and for the same SNR and number of samples *N*, the probability of detection will be lower when PU transmits with lower Tx power and vice versa. This is because higher Tx power means higher energy at the position of SU, which consequently results in a higher probability of signal detection. Also, from Figure 3(c) we can notice that the signals transmitted with higher Tx power (10 W) and impacted by higher NU ($\rho = 1.05$) can achieve a lower probability of detection (Figure3a) than those transmitted with lower Tx power (100 mW) impacted by the lower NU factor ($\rho = 1.01$). This further confirms the impact of NU on the ED process in the case of the bit and power loading (RA and MA) OFDM-based systems which adjusts Tx power and the constellation order during operation.

According to the results presented in Figure 3, in order to preserve the QoS, RA and/or MA OFDM systems change modulation constellation and/or Tx power, respectively. To achieve the equal SNR at the position of SU, the signals modulated with a higher constellation order are generally transmitted with higher Tx power and vice versa (Figure 3c). For example, to achieve a specific SNR equal to -15 dB (Figure 3), different Tx powers with corresponding modulations can be used in channels impacted by different noise levels at the position of SU. For channels with higher noise, higher Tx power with a higher constellation order can achieve equal SNR as in the case of channels impacted by low noise where the lower Tx power with lower OFDM constellation can be used (Figure 3). Hence, modulation constellation does not have a direct impact on the probability of detection of joint RA and MA systems. However, the results presented in Figure 3 show that the increase of PU Tx power for the same modulation constellation is followed by the increase in the probability of detection (P_{d_i}) for the case of equal channel conditions (same SNR and NU factor). Hence, the OFDM modulation constellation has an indirect



(a) **(b)**

(c)

Figure 3. ROC curves for joint RA and MA OFDM systems impacted by different values of NU factors and transmitted with: (a) Tx power of 0.1 W and QPSK modulation; (b) Tx power of 1 W and 16-QAM modulation; (c) Tx power of 10 W and 64-QAM modulation

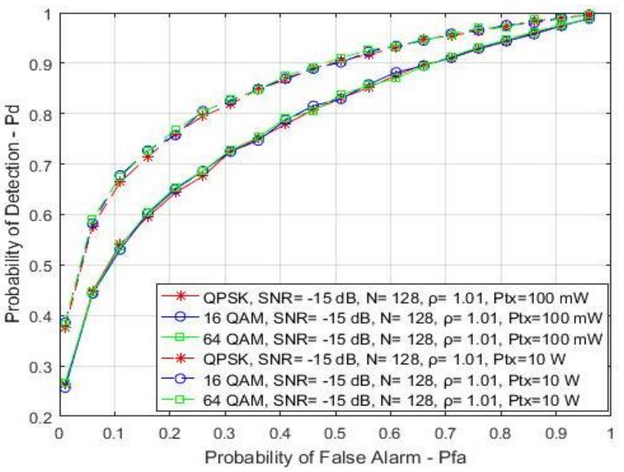
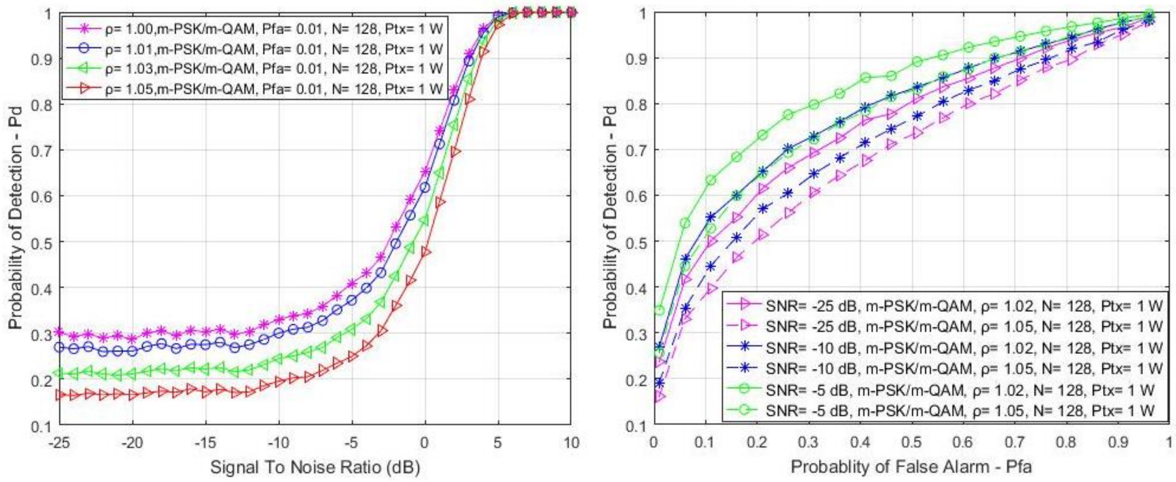


Figure 4. ROC curves for MA systems impacted by equal NUs for different Tx powers and OFDM modulations

impact on the probability of detection, since achieving equal SNR for modulations with higher constellation must be followed by higher Tx power and higher Tx power results in a better probability of detection (P_{d_i}).

Additional analyses for MA OFDM systems have been performed with signals impacted by the fixed NU variation (ρ =1.01). The results are presented in Figure 4, where it is assumed that each OFDM modulation



(a) **(b)**

Figure 5. (a) SNR vs. probability of detection for OFDM signals impacted by different NUs in RA systems; (b) ROC curves for different values of SNR for an RA OFDM system transmitting signals modulated with m-PSK/m-QAM modulations and impacted by two different NU factors

(QPSK, 16QAM, 64QAM) for specific Tx power (100 mW or 10 W) can achieve SNR of -15 dB or better. According to the results presented, the MA systems transmitting with the same OFDM modulation, but with different Tx powers will have different probabilities of detection.

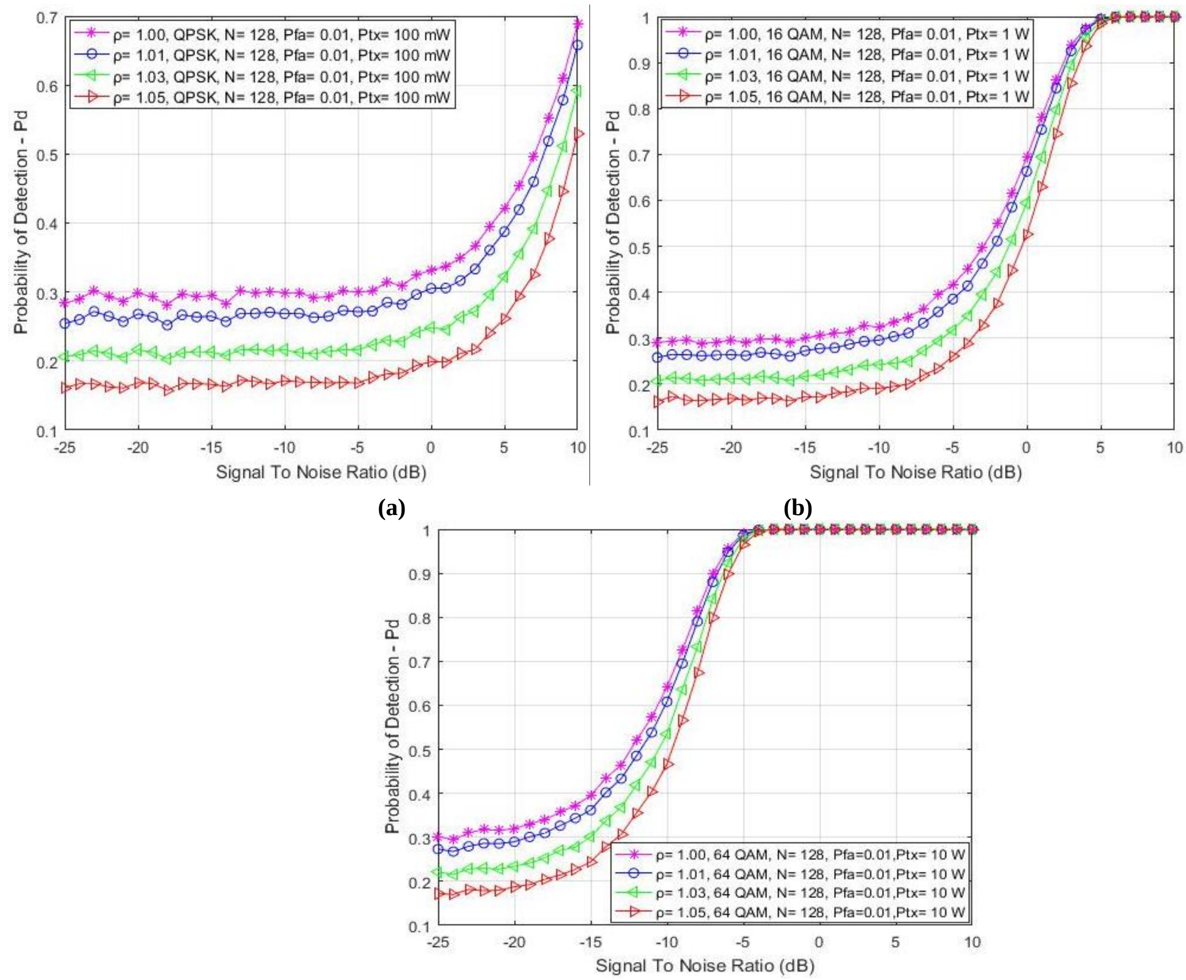
A higher probability of detection for the same false alarm probability will have an OFDM modulation transmitted with higher Tx power. This means that Tx power adjustment in MA systems significantly impacts the probability of detection, even when there is an impact of NU variation (Figure 4).

7.3. The effect of signal-to-noise ratio on the energy detection process

Further simulations related to the impact of SNR at the position of SU on the ED process have been performed. The results obtained, presented in Figure 5(a), show the impact of SNR at the position of SU on the probability of signal detection (P_{d_i}) for RA OFDM systems. As explained in the previous section, for the fixed Tx power of PU (1 W) and some fixed value of the probability of false alarm (P_{fa_i}= 10%), the probability of detection (Figure 5a) will be the same for any modulation and corresponding constellation (m-QAM/m-PSK modulation). However, the simulation results presented in Figure 5(a) show that for lower values of SNR, the probability of detection will be low (less than 30%) for every modulation constellation and will increase with the improvement of SNR. This is expected since lower SNR means lower energy of PU signal at the position of SU, which diminishes accurate signal detection and consequently lowers the probability of detection.

Additionally, for the signals with the same SNR which are more impacted by NU, the probability of detection will be further degraded due to the higher impact of NU in AWGN which consequently lowers the overall SNR during the ED process (Figure 5(a)). Also, Figure 5(b) presents ROC curves for different values of SNR (-25 dB/-10 dB/-5dB) and fixed PU Tx power (1 W) of OFDM signals modulated with m-PSK/m-QAM modulations and impacted by different NUs. According to the results, for noisy channels (having low SNR at the position of SU), the probability of detection will be lower due to the negative impact of the noise in the ED process. This means that for RA OFDM systems, independently of NU, the overall level of noise (AWGN) has a dominant impact on the ED process and higher noise levels can significantly degrade ED performance. This is because a higher SNR for the same Tx power of PU means less noise at the position of the SU user, which consequently results in a higher probability of detection. Besides the dominant impact of the overall level of AWGN, Figure 5(b) further confirms the non-negligible impact of NU which additionally contributes to ED performance. Figure 5(b) shows that for higher NUs, the probability of detection will be lower for signals with lower SNR. This means that the combination of low SNR with high NU negatively impacts on the ED performance of RA OFDM system.

For joint RA and MA OFDM systems, the influence of SNR on the probability of detection of OFDM signals impacted by different NUs is presented in Figures 6(a) – (c). The results presented there show that independently of the PU Tx power and OFDM modulation, higher noise fluctuations (characterized by a higher NU factor) will lower the probability of detection for any SNR level which is below the SNR threshold (ensures guaranteed PU



(c)

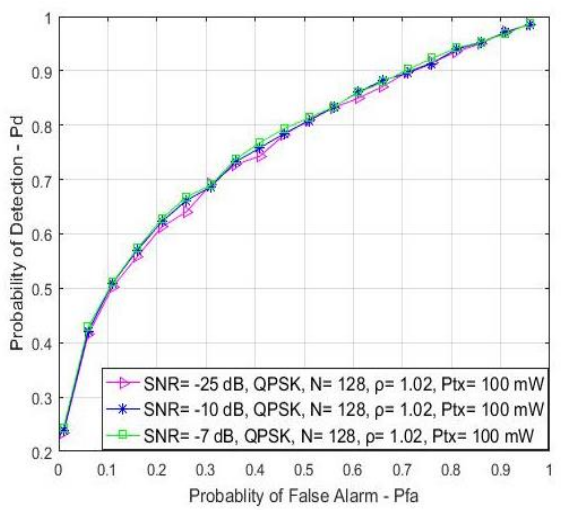
Figure 6. Influence of SNR on the probability of detection for OFDM signals impacted with different NUs and transmitted with Tx power of: (a) 0.1 W; (b) 1 W; (c) 10 W

detection). NU variations impact each OFDM signal independently of its Tx power and modulation order; however, for signals with lower Tx power, this impact is more evident, as reflected in the lower probabilities of detection.

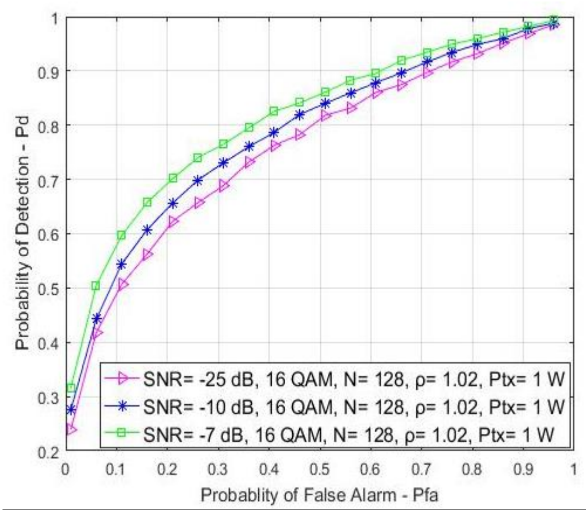
Additionally, for different Tx power levels, there is an SNR threshold above which the probability of PU signal detection can be guaranteed (Figures 6a – c). This SNR threshold is dominantly impacted by the level of Tx power and it is lower for the higher Tx powers of PU signal (5 dB for Tx power of 1 W and – 5dB for Tx power of 10 W). As indicated in Figure 6, the OFDM modulation order has no impact on the SNR threshold, since the modulation order does not have a direct impact on the probability of detection (relations 19, 25, 26, 31).

The influence of different Tx powers and SNR levels on detection probability of joint RA and MA OFDM systems is presented with ROC curves in Figure 7. The obtained results are obtained for different SNRs (-7 dB/-10 dB/-25 dB) of m- PSK/m-QAM modulated signals impacted by equal NU (ρ =1.02) in case of PU signal transmission at specific Tx power levels (0.1 W, 1 W, 10 W). The results confirm that the level of PU Tx power (relations 19 and 26) and SNR (relations 25 and 31) at the location of the SU have a significant impact on the probability of detection in OFDM systems. As expected, for higher levels of Tx power and for lower values of SNR, the probability of detection will be higher and vice versa. However, in Figure 7(a) we can see that for low values of Tx power (100 mW), the probability of detection at the position of the SU cannot be improved without a significant increase of the SNR (above 5 dB).

On the other hand, Figure 7(c) shows that for significantly a higher Tx power (10 W), signal detection in the ED process can be guaranteed (probability of detection P_{d_i}=100 %) for every SNR level above -7 dB. Such results confirm the impact of noise power on the quality of the ED process. Figure 8 presents the influence of SNR on the probability of detection for MA OFDM systems transmitting at two different Tx power levels (1 W/10 W) over a channel with equal channel conditions (equal NU factor ρ =1.01), the probability of false alarm (P_{fa_i}=10 %) and



(a)



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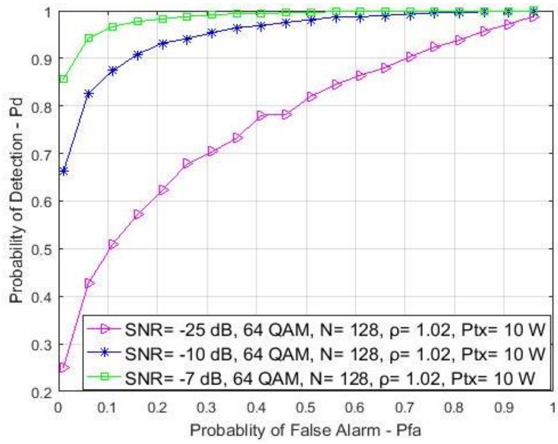


(c)

Figure 7. ROC curves for OFDM signals transmitted in joint RA and MA systems with Tx power equal to: (a) 0.1 W; (b) 1 W; (c) 10 W

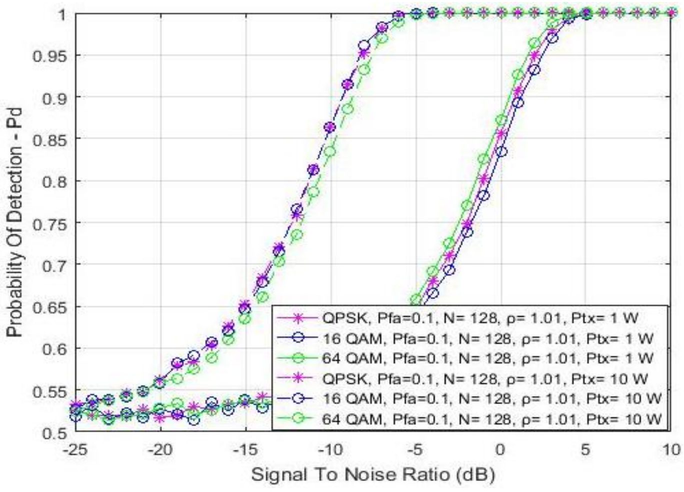
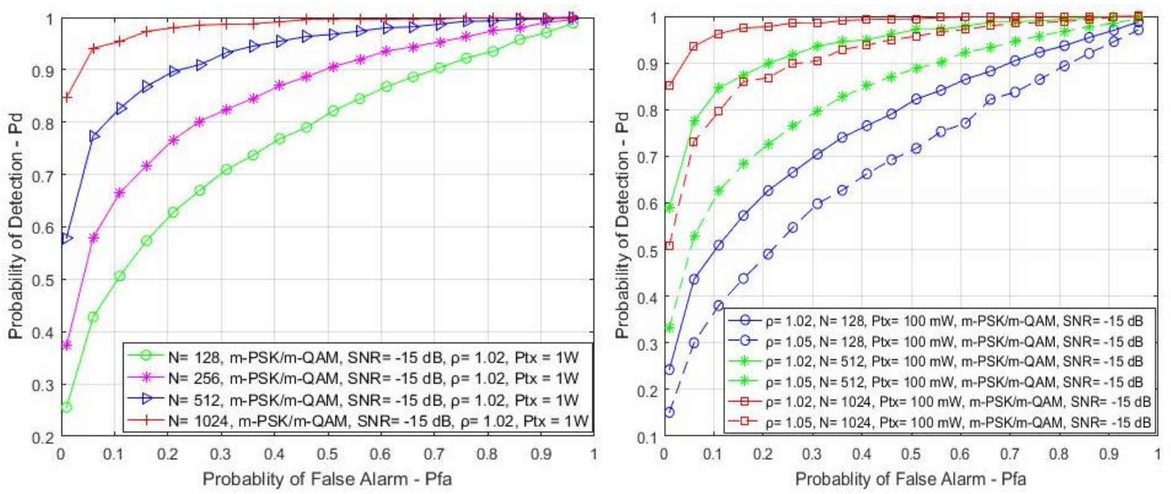


Figure 8. Probability of detection vs. SNR for MA OFDM system transmitting at two different Tx power levels

different OFDM modulations. The presented results show that OFDM modulations do not have any impact on the probability of detection in MA systems for any SNR level if modulated signals are impacted with the same NU and transmitted with the same Tx power. However, a higher probability of detection can be noticed for signals of the same constellation order transmitted at higher Tx power, since higher Tx power means better SNR at the position of the SU. For lower SNR at the position of the SU, the MA OFDM system that transmits with higher Tx



(a) **(b)**

Figure 9. ROC curves for m-PSK/m-QAM modulated signals transmitted with fixed Tx power and detected with different number of samples for: (a) equal NU (ρ=1.02); (b) two different levels of NUs (ρ=1.02, ρ=1.05)

power means better SNR at the position of the SU. For lower SNR at the position of the SU, the MA OFDM system that transmits with higher Tx power will have a better probability of detection. Hence, in MA OFDM systems, transmission with higher Tx power improves the probability of detection for any SNR level at the position of the SU. However, this might have a negative impact in terms of interference and PU power consumption.

7.4. The effect of the number of samples on the energy detection process

Further analyses were dedicated to the impact of the number of samples on the ED capabilities of SU. In Figure 9, ROC curves for m-PSK/m-QAM modulated signals transmitted with fixed Tx power (1 W/100 mW) and detected with a different number of samples for different NU levels are presented. According to Figure 9(a), the number of samples has a strong impact on the ED performance of RA OFDM systems. In the case of channels with equal channel characteristics (equal SNR and NU), the probability of signal detection increases when a higher number of samples is used in the ED process of RA OFDM systems. This is because a higher number of samples means a higher number of attempts in a specific period during which the signal of the PU can be detected.

Additionally, in Figure 9(b) ROC curves for m-PSK/m-QAM modulated signals in RA OFDM systems detected with the different number of samples for two different levels of NU variations (ρ=1.02, ρ=1.05) are presented. It can be observed that for higher values of NU (ρ=1.05), a higher number of samples must be used in order to achieve the probability of detection equal to the detection probabilities in channels impacted by lower NU (ρ=1.02). This is because a higher NU results in a higher degradation of the signal received, which requests more sensing attempts (number of samples) for accurate ED of the PU signal power which will have a better probability of detection. Hence, in MA OFDM systems, transmission with higher Tx power improves the probability of detection for any SNR level at the position of the SU. However, this might have a negative impact in terms of interference and PU power consumption.

In Figure 10, ROC curves for different OFDM modulated signals detected with a different number of samples and for a signal transmitted at three different Tx power levels are presented. The results show that in joint RA and MA OFDM systems, a decrease in the number of samples and Tx power leads to a decrease in the probability of detection and vice versa. This is in line with theoretic analyses (relations 26 and 19) according to which Tx power and number of samples (N) directly impact the probability of detection. A higher Tx power for specific OFDM modulation means more energy at the position of SU in the ED process, while a higher number of samples N means more attempts for ED detection of the PU signal. Also, for some specific combination of Tx power, SNR and NU, there is a threshold N in the number of samples above which the probability of detection can be guaranteed for every OFDM modulation (P_{d_i} = 100%). In the case of simulation scenario (Figure 10) with an SNR level equal to - 15 dB, this number of sample threshold will be lower for OFDM modulations having a higher constellation, since such modulations must be transmitted with higher Tx power in order to satisfy set SNR demand.

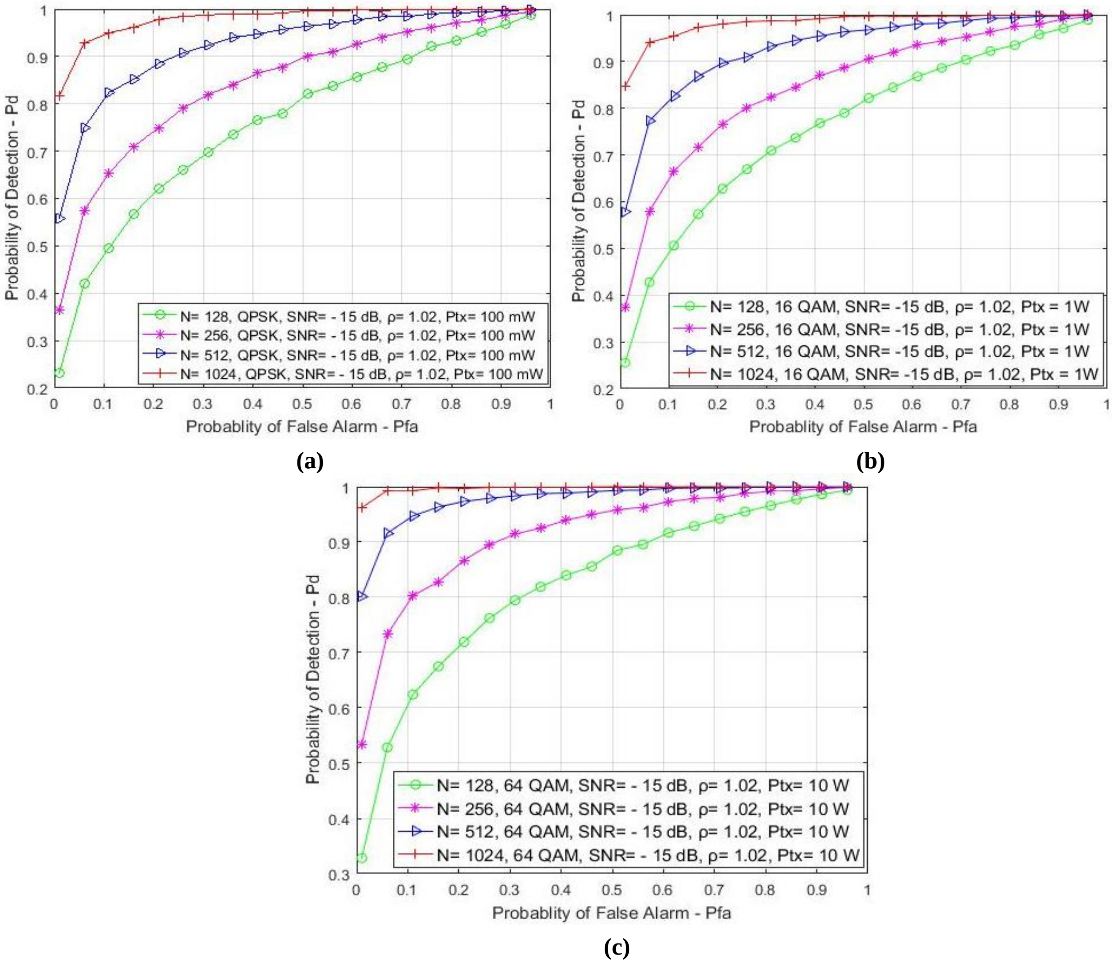


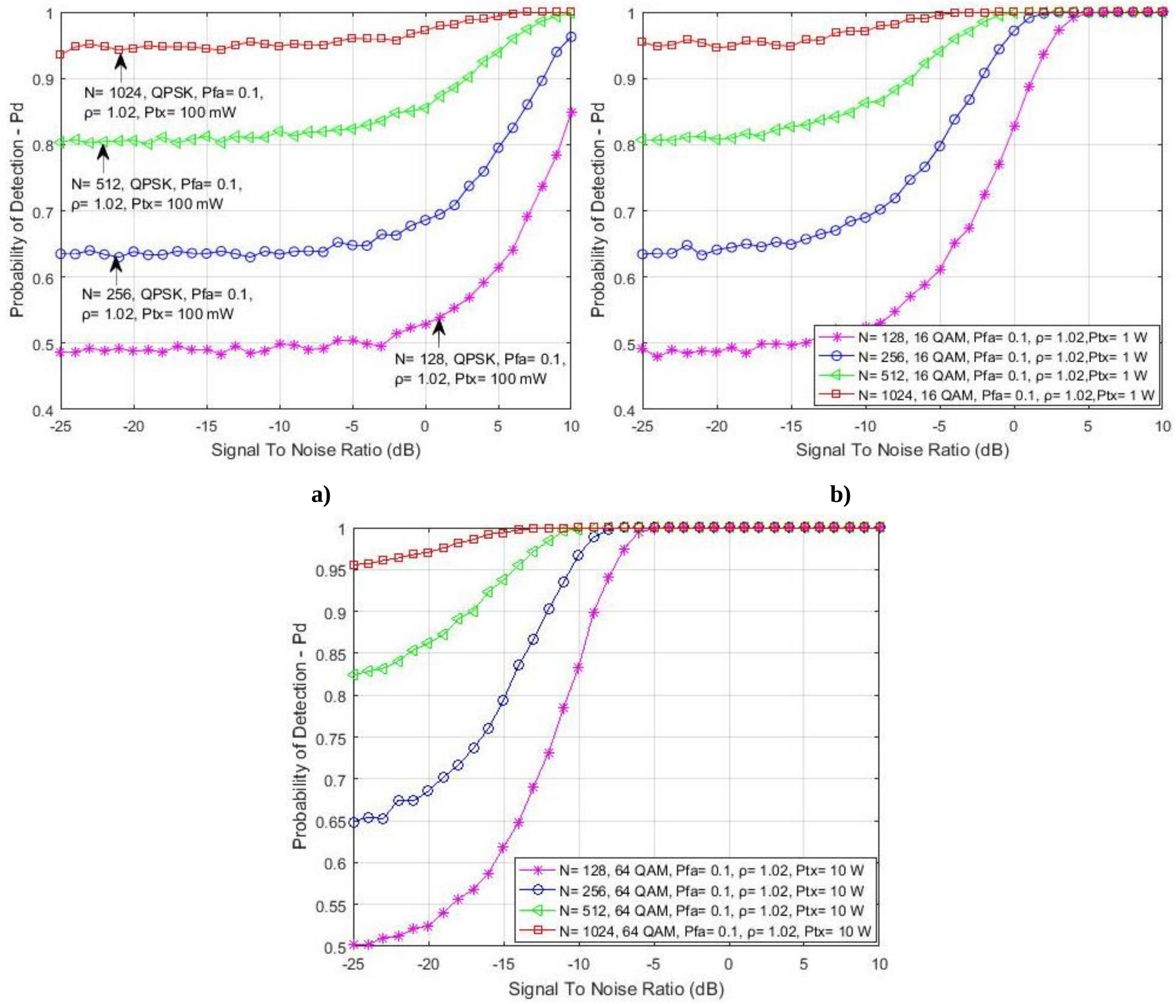
Figure 10. ROC curves for different OFDM modulated signals detected with different number of samples and transmitted at Tx power equal to: (a) 0.1 W; (b) 1 W; c) 10 W

Figure 11 presents the impact of SNR and the number of samples on the probability of detection (P_{d_i}) for RA and MA OFDM system. The results are obtained for different Tx power levels and for the set probability of false alarm equal to P_{fa_i}=0.1 and fixed NU variation equal to 2% of AWGN. Based on the results obtained, a higher probability of detection can be achieved for a higher number of samples and higher SNR in case of any OFDM modulation (Figure 11). Since a higher SNR is a direct result of higher Tx power, the SNR threshold above which the probability of detection can be guaranteed (P_{d_i}=100%) will be lower for signals sampled with a higher number of samples. Even for lower Tx powers, there are a number of samples which can guarantee the probability of detection if SNR is above the minimal threshold (Figure 11a).

7.5. The effect of the probability of false alarm on the energy detection process

The last analyses take into account the impact of the probability of false alarm on the probability of detection for different OFDM system design options. According to the definition, the probability of false alarm (P_{fa_i}) is the probability that the SU incorrectly declares that a PU is present when the PU is actually absent. When the PU is actually present and the SU correctly declares that the PU is present, the probability that the SU incorrectly declares that a PU is present increases. For that reason, in Figures 2-4, 7, 9 and 10, the increase in the probability of detection (P_{d_i}) is followed by the increase in the probability of false alarm (P_{fa_i}).

Some ED approaches are based on setting the probability of false alarm (P_{fa_i}) to some predefined value which must be satisfied during the ED process. Although it is preferable that the probability of a false alarm be kept at the lowest possible levels, values of up to 20% for false alarm probability are reasonable and practically used, which is the reason for selecting such values for analyses.



c)

Figure 11. Impact of SNR and number of samples on the probability of detection for joint RA and MA system of OFDM signal transmitted at: (a) 0.1 W; (b) 1 W; (c) 10 W

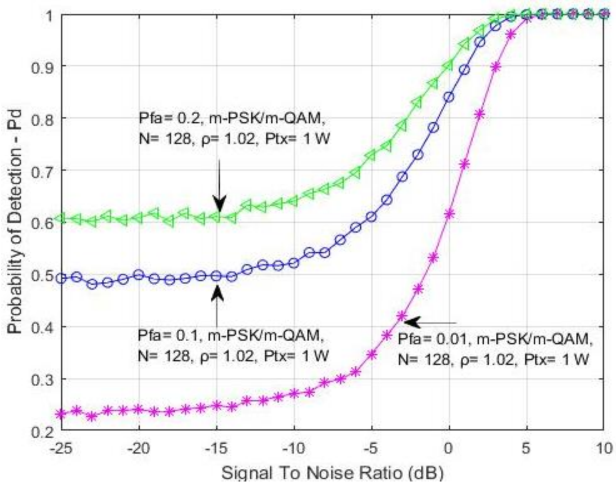


Figure 12. Impact of SNR on the probability of detection for RA OFDM systems with different probabilities of false alarm

In Figure 12, the relationship between SNR and the probability of detection has been presented for RA OFDM systems with respect to different values of probabilities of false alarms (1%, 10% 20%). The results are obtained for the equal number of samples (N=128) and equal NU factor (ρ=1.02). Taking into account some specific SNR (e.g. – 15 dB), the results presented in Figure 12 show that the probability of detection will be higher if the

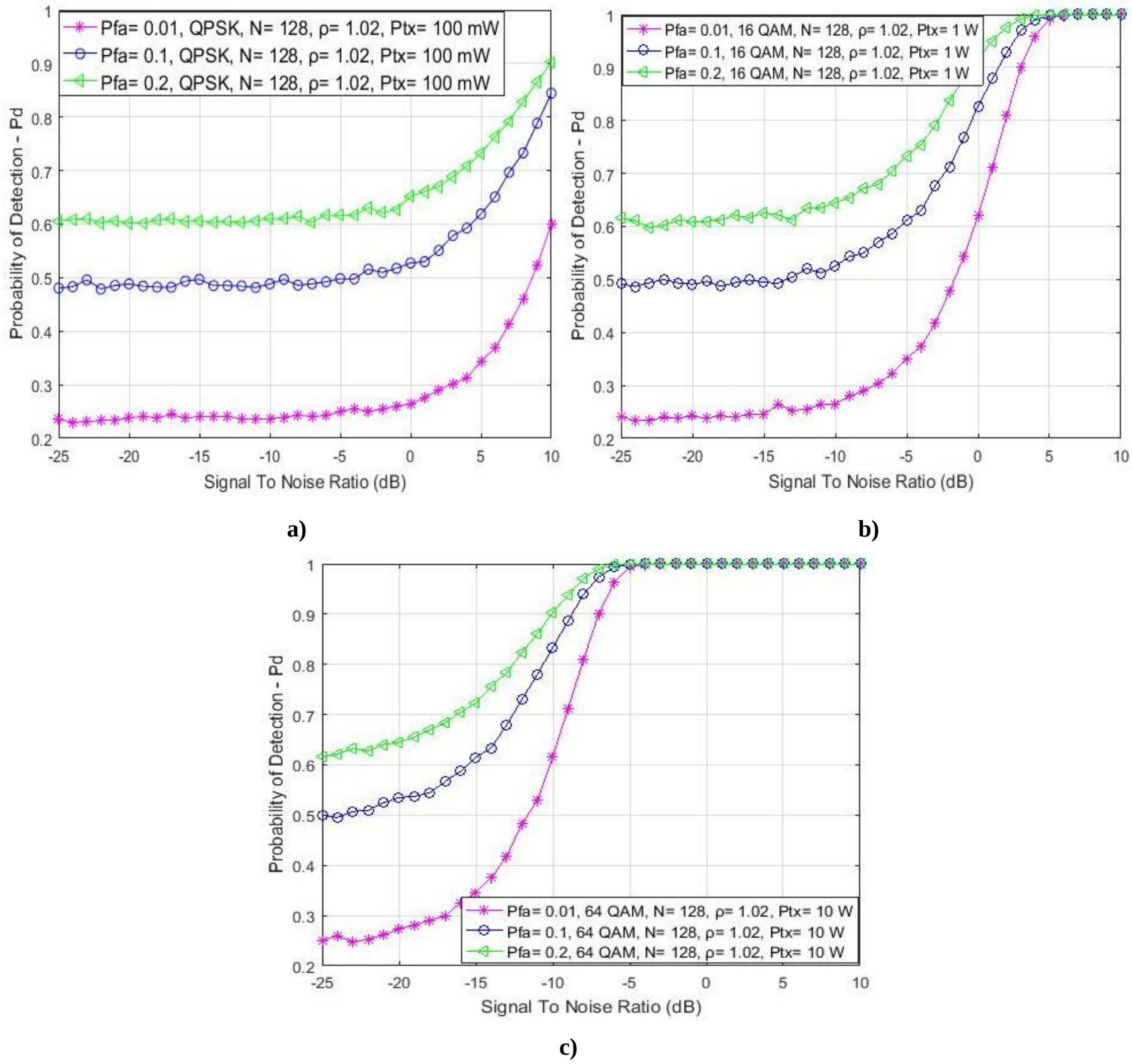


Figure 13. Impact of SNR and the probability of false alarm on the probability of detection for joint RA and MA OFDM systems transmitting at: (a) 0.1 W; (b) 1 W; (c) 10 W

probability of false alarm is higher in case of transmission at fixed Tx power (RA OFDM systems). This means that for some SNR level at position of SU, correct ED estimations in periods when the PU is active have a higher impact on ED performance than incorrect ED estimations in the periods when the PU is not active.

The interdependence between SNR and the probability of detection for joint RA and MA OFDM systems transmitting at different Tx power levels has been presented in Figure 13. The results are obtained for different probabilities of false alarm under equal channel conditions (NU factor ρ=1.02) and the number of samples (N=128). In Figure 13 we can notice that setting the probability of false alarm to a higher value increases the probability of detection for any Tx power and the corresponding modulation order. However, a higher probability of the false alarm also increases chances of a wrong decision of the SU and trade-off in selecting false alarm probability must take place. Also, the SNR threshold above which probability of detection is guaranteed is lower for signals with higher Tx power and a higher probability of false alarm (Figure 13). Additionally, for each of OFDM modulation schemes, Figure 13 shows there is an SNR threshold above which the probability of detection is guaranteed ($P_{d_i} = 1$).

According to the results presented, the probability of a false alarm does not have any impact on this threshold. This threshold is lower for modulation schemes with higher constellation number since these modulation schemes must be transmitted at higher Tx power if the same SNR needs to be kept. For these reasons, the ED of OFDM signals based on a higher probability of a false alarm with a higher constellation order can be detected at lower SNR levels for the case of joint RA and MA OFDM systems.

8. Discussion and future research challenges

This section contains discussions concerning performance issues and future scientific challenges related to the ED method. The discussion is based on the simulation results presented in the previous section for the ED performance of different OFDM system designs. Table 6 summarizes the main drawbacks of the ED method and possibilities for improvements of spectrum sensing based on ED.

The simulation results presented in Figures 2, 3, 5(b) and 9 (b) prove that the main ED drawback is the degradation of detection accuracy with the increase of noise power variation (NU). This susceptibility of ED to the uncertainty in noise power can be improved through dynamic adaptation of the decision threshold (Table 6). An appropriate selection of the detection threshold can provide the primary user with adequate protection, reduce spectrum-sensing error and improve spectrum utilization. Considerable research efforts related to this topic have been presented so far in literature [65-67]. In [65] the authors analyze the selection of the threshold based on the bounding of the probability of false alarm and then maximizing the detection probability by iteratively updating the value of the threshold.

Although the paper lacks an explanation of noise level estimation, threshold selection is dynamically adapted to the noise level of the received signal. To minimize the spectrum- sensing error in the presence of noise, dynamic selection of the threshold using a discrete Fourier transform filter bank method is proposed in [66]. To set a new value of the sensing threshold, the proposed approach uses the gradient-based updates. [67] proposes an adaptive threshold detection method based on an image binarization technique which dynamically estimates the threshold based on previous iteration decision statistics and other parameters such as SNR, the number of samples, and the targeted probabilities of detection and false alarm. To cope with NU, a double-threshold technique is proposed in [68, 69], defining free spectrum if the energy of the samples is smaller than the lower threshold level, and occupied spectrum if the energy of the samples is higher than the higher threshold level. Although the proposed algorithm decreases the collision probability, its detection performance is not acceptable for low SNR values and the criteria for selection of the two threshold levels is not explained. The author in [70] proposed an adaptive threshold that consists of two control parameters: the Constant Detection Rate (CDR) method which sets the target probability of detection and the Constant False Alarm Rate (CFAR) method which consists of fixing a target probability of false alarm. Then, the selection of the threshold is based on the minimization of spectrum-sensing error. Since noise power constantly changes over time, the dynamic adaptation of a detection threshold is a challenging task and no optimal algorithms have been proposed so far.

Hence, advancements in the dynamic threshold adaptation algorithms for better robustness to the NU remains an open research issue for ED spectrum sensing. Additionally, since previously mentioned related works validate the dynamic selection of the threshold through simulations, and several system parameters that are assumed constant in simulations may vary over time, a real scenario validation of newly-proposed algorithms must take place. The research focused on the dynamic selection of the threshold based on measuring the real power of the noise level present in the signal received during the detection process, shows an increase in the probability of detection compared to the ones of ED with a static threshold [27].

Since ED performance strongly depends on the reliability and accuracy of the noise level estimate, which is used for computing of SNR, it was important to evaluate ED under certain NU scenarios as is done in this work for different OFDM system designs. According to the results presented in Figures 5(a), 6, 11 -13, another important drawback of the ED method is the inability to detect signals at low SNRs at the position of SU, also proven in [71], [72]. Simulation results show that if the signal power is under a certain SNR value (known as SNR wall [73]), the energy detector cannot distinguish the signal from a slightly larger noise power, regardless of the sensing period duration or the used number of samples [22]. Since measuring NU is challenging because this parameter varies with time, ED techniques require an estimate of the noise power to compute SNR. This estimation can be done using a channelized radiometer in the frequency domain [74, 75], which divides the total frequency band into smaller channels and then integrates the energy from each channel separately using a radiometer. Also, the noise level may be estimated from guard bands. Due to the impact of the noise power estimation error [21], an adaptive noise level estimation concept is proposed in [76] based on multiple signal classification algorithms used to separate the signal and noise subspaces and estimate the noise floor. However, the development of new methods for accurate and reliable noise level estimate for ED spectrum sensing are missing. New methods which offer more precise noise level estimation during the ED process can contribute to the improvement of signal detection at lower SNRs (Table 6).

A further ED drawback is related to the degradation of detection accuracy for a low number of samples (Table 6), which is also proven by the simulation results presented in Figures 9 - 11. To achieve a high probability of

Table 6. Main drawbacks, research challenges and possible improvements of the ED method

Main ED drawbacks	ED research challenges	Expected improvements
Degradation of detection accuracy due to variations in noise power (NU)	Development of new dynamic threshold adaptation algorithms and validation in real environments	Improved detection accuracy in environments impacted by noise fluctuations; Better PU protection
Unable to detect signals with low SNR	Development of new methods for accurate and reliable noise level estimate	Improved detection of signals at lower SNRs
Degradation of detection accuracy for a low number of samples (or short sensing duration)	Improving ED through reduction in sensing time (number of samples)	Reduces energy consumption for cognitive WSN; Increases throughput of SU

detection, ED requires a large number of samples or longer sensing period [68, 77, 78]. However, during the sensing period, data transmission is stopped, thus increasing end-to-end delay and reducing SU throughput. Ideally, the sensing time should be as short as possible, which negatively affects the detection performance (as presented in Section 7.4) and requires more frequently sensing period repetition. Hence, in a CRN, periodic sensing intervals and the number of samples (sensing time) are optimized to maximize sensing accuracy and/or SU throughput. Adjusting the periodic sensing interval in ED affects the capability of the SU to exploit the spectrum opportunities [71, 79, 80]. Moreover, the number of samples influences ED performance in terms of the probability of detection (as shown in Section 7.4). The throughput sensing trade-off for the ED method is analyzed in [81], where the number of samples used is optimized to maximize the throughput for the SUs under the restriction that the PUs are appropriately protected. Still, identifying the sensing period and how frequently it should be performed (sensing frequency) is a crucial design element which requests a deeper investigation in order to improve ED spectrum sensing (Table 6).

The ED drawback concerning the degradation of detection accuracy for a low number of samples is additionally related to the possibility of implementing the ED method in cognitive wireless sensor networks (CWSN). Although using ED as a sensing method can be most suitable for implementation in CWSN where low power sensor nodes can benefit from the low computation complexity of the ED method [82-84], a larger number of samples for accurate detection negatively contributes to the energy efficacy of the sensor nodes. In CSWN, keeping the transceiver of the sensor node active just for spectrum sensing causes excessive power consumption [85]. Hence, only the development of novel approaches which will combine the low computation complexity of ED with minimum sensing duration can ensure the applicability of the ED method in resource-constrained CWSN requesting high power efficiency towards maximizing the sensors' lifetime.

Besides ED, several different narrowband local spectrum sensing methods have been proposed to enhance the reliability and accuracy of available spectrum detection. Table 7 presents a performance comparison of prominent non-cooperative local spectrum sensing methods. Compared to the *Matched filter detection* (*MFD*) method [7, 86-92], ED is far less accurate especially for the detection of low SNR signals. The *MFD* method is the optimal technique for local spectrum sensing when the PU signal is known since this method ensures very good detection performance for a small number of samples. However, compared to the ED method, its main drawback is higher computational complexity and the need for exact prior knowledge of the PU signal, which may not always be obtainable since the PU and the SU do not actively communicate. Additionally, different receivers must be used to receive different signal types which further increases implementation complexity, sensing time and power expenditure of the *MFD* method.

8.1 Comparison with other non-cooperative spectrum sensing methods

Another sensing method that can be viewed as a simplified *MFD* method is *Waveform-based* detection method [82, 93-95]. This method has better accuracy for shorter sensing time than the ED method (Table 7). Although less information about the PU signal is required compared to *MFD*, this method still needs information about PU signal in terms of signal pattern (transmitter pilots, preamble, etc.) of every PU. In case of many different PUs, a signal pattern database may be too large and complex for single SU management. Additionally, this method requests exact synchronisation between PU and SU and compared to the *MFD*, *Waveform-based* sensing has a lower complexity, which is however more complex than the ED method [96].

Unlike ED, the *Cyclostationary detector* can differentiate the primary signal from interference and noise using the periodicity property in low SNRs [92, 97-101] (Table 7). The *cyclostationary detector* is an ideal method for the detection of low SNR signals since it is significantly more robust against NU than ED because noise is typically not cyclostationary [101]. The *Cyclostationary detector* requires a priori knowledge of the PU signal

Table 7. Performance comparison of non-cooperative local spectrum sensing methods and the ED method

Parameter	Matched filter detection method	Cyclostationary feature method	Entropy-based detection method	Waveform-based detection method	Goodness of Fit (GoF) test method	Energy detection (ED) method	Eigenvalue detection method
Detection accuracy at all SNR levels	Optimal for known PU	Very good (the best for low SNR)	Good	Very good	Moderate	Weak at low SNRs	Moderate
Request prior information about PU signal	Yes, Perfect	Yes	No	Yes	No	No	No
Sensing time (number of samples) for accurate detection	Low	High	High	Low	Low	High	High
Robust against NU	Yes	Yes	Yes	Yes	No	No	Yes
Computational complexity	High	The most complex	Moderate	Moderate	Low	The least complex	High

which makes this detection method more computationally complex than the matched filter and especially the ED method [82, 90, 101]. In order to get a good detection performance, the *Cyclostationary detector* needs a large number of samples which increases sensing time, power requirements and is not cost-effective especially for CWSNs.

The *Entropy detector* (Table 7) has better detection accuracy than ED since it detects signals with very low SNR; however, a priori knowledge of the PU is required [90]. The algorithms required for this detector are therefore more complex than for ED. This detector type needs a high number of samples for accurate detection; however, it is more robust to the NU than ED [102-104].

Different covariance matrix or *Eigenvalue-based detection* methods have been widely investigated for blind spectrum-sensing methods [82, 105-111], most of which perform better than the ED in terms of detection accuracy (Table 7). Compared to ED, *Eigenvalue-based detection* is more robust to the NU problem since it utilizes the correlation structure inherent in the received data for sensing and differences in the eigenvalues of the statistical covariance matrix of signal and noise. As in the case of ED, there is no requirement of a priori information about the PU signal, but the method has large computation complexity due to a high number of samples needed for the computation of the covariance matrix and the eigenvalue decomposition of the covariance matrix. Reduction in the sensing time for some new *Eigenvalue-based methods* is proposed in [112].

Goodness of fit (*GoF*) *test-based* sensing utilizes the distribution characteristics of the background noise (Table 7). As for the ED method, *GoF* does not request knowledge of the PU signal; however, it is able to obtain a better detection performance even with a small number of samples (approximately 2.4 times lower than the ED method) [82, 113-118]. Many types of *GoF* tests are proposed in the literature, with the main difference in how to calculate the test statistic, i.e. the distance between the empirical cumulative distribution (CDF) of the PU signal observations made locally at the SU and the noise CDF [119-122]. The computational complexity of the *GoF* method is low and similar to the ED method which makes the *GoF test-based* method valuable for practical implementations.

This comparison of different local spectrum sensing techniques and the ED technique shows that ED has many weaknesses. However, ED is the most commonly used spectrum sensing technique as it does not require any information about the nature of the PU signal. In addition, it does not involve complicated signal processing and has low complexity making it interesting for practical implementation. The abovementioned fundamental challenges and many others need to be precisely addressed in order to exploit the all possible advantages of the ED method.

9. Conclusions

Spectrum sensing in the ED process can be impaired by the NU which is manifested as a random fluctuation of noise power in space and time. In this work, an overview of the impact of NU on the performance of the ED process has been presented. The analyses are performed through different simulations based on the developed algorithms which simulate the ED process of OFDM signals performed for three different OFDM system design options (RA, MA, and joint RA and MA).

The presented review analyses show that the NU had a significant impact on the probability of PU detection for each of OFDM system designs. Higher levels of NU decrease the probability of signal detection which is lower for signals transmitted at lower transmit powers. The results of the analyses also show that for higher SNR at the position of SU, the probability of ED will be higher. The number of samples has an important impact on ED since higher probabilities of signal detection have been obtained for a higher frequency of sampling during the ED process. The overall conclusion is that the probability of PU energy detection for any OFDM system design will be higher for the reception of OFDM signals having lower NU, higher SNR ratio, which are transmitted at higher PU transmit power and detected with a higher number of samples.

Hence, the main ED drawbacks in terms of degradation of the detection accuracy caused by the variations in noise power (NU), the inability of detecting OFDM signals with low SNRs and the reduction of detection accuracy for a low number of samples have been confirmed through extensive simulations. Literature overview was followed by the discussion related to the main research challenges which can contribute to the improvement of major ED drawbacks. The discussion is further enriched with a comparison between the ED method and other local spectrum-sensing methods using benchmarks such as detection accuracy, knowledge of PU signal, sensing time, robustness to a low SNRs and computational complexity. The comparison shows that there is no ideal spectrum-sensing method and that ED has a lower detection accuracy, higher sensing time and lower robustness at low SNRs compared to most of the spectrum-sensing approaches analyzed. However, the lowest computational complexity, lack of prior knowledge of PU signal and applicability for detection of OFDM signals, justifies further investigations to improve the ED method in order to keep the status of the most frequently used local spectrum sensing approach.

Since the static threshold was used for the detection of PU signals in the ED process analyzed, our future work will be dedicated to the comprehensive analyses of the impact of the dynamic threshold on ED performance of the OFDM signals.

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